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Research on Complex Indoor Environment Mapping Based on LiDAR and RGB-D Camera Fusion

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Abstract: With the continuous progress of science and technology and the improvement of social productivity, mobile robots have been widely used in military, medical, logistics and other fields. High-precision mapping technology for complex indoor environments has become one of the focuses of scholars' attention and research hotspots. Traditional single sensors (e.g., LiDAR or cameras) have limitations in dynamic, low-texture or light-varying environments. In this paper, we propose a mapping method based on the multi-sensor fusion of LIDAR (RPLIDAR A2M8-R3) with RGB-D camera and odometry to improve the accuracy and robustness of mapping in complex indoor environments by fusing the accurate distance measurement of LIDAR with the rich visual information of camera. Firstly, a ROS-based robotic hardware and software platform is constructed, integrating LiDAR (RPLIDAR A2M8-R3) and RGB-D camera. Secondly, sensor data preprocessing such as LiDAR is optimised by various algorithms. Finally, the iRTAB-Map fusion modelling strategy is used to achieve efficient fusion of multi-source data for map building. Experiments show that the fusion system is better than the single-sensor scheme in terms of 2D raster map accuracy and 3D point cloud completeness, and the navigation accuracy is not only high but also the real-time observation of obstacles and road conditions through the camera, which provides reliable technical support for indoor complex scene mapping.

Keywords: Multi-sensor fusion; LiDAR; RGB-D camera; SLAM; indoor mapping.

1. Introductory

1.1. Background and significance of the study

With the rapid development of artificial intelligence and robotics, the market demand for robots with autonomous navigation capability continues to grow, and high-precision mapping technology for complex indoor environments has become a research hotspot. Traditional single sensors (e.g., LiDAR or cameras) have limitations in dynamic, low-texture or light-varying environments. [1-2]However, complex indoor environments usually suffer from structural breakage, uneven lighting, and dynamic obstacles, which make it difficult for a single sensor (e.g., LIDAR or vision camera) to meet the demand for high-precision mapping. [3-5] LiDAR can provide accurate distance information but lacks semantic and colour information; RGB-D cameras can capture rich 3D visual data but are susceptible to light and dynamic object interference. Therefore, fusing the advantages of multi-sensors to build a robust and efficient map building system has important research value.

1.2. Research status

Multi-Sensor Fusion (MSF) compensates for the limitations of a single sensor by integrating heterogeneous sensor data. In the field of simultaneous localisation and mapping (SLAM), the fusion of LiDAR and vision has become the mainstream direction. For example, LIO-SAM achieves high-precision positioning by tightly coupling LiDAR and IMU, and R2LIVE fuses LiDAR, camera and IMU to build dense point cloud maps. However, most of the existing studies focus on the fusion of multi-line LiDAR and vision, and there are fewer studies on the fusion of low-cost single-line LiDAR and RGB-D camera for map building. [6-9] Based on this, this paper proposes a lightweight multisensor fusion scheme for narrow and dynamic complex indoor environments. In conclusion, multi-sensor fusion, as an important information fusion technology, has been widely used in military, aerospace, navigation, intelligent transport and other fields. With the continuous progress and innovation of technology, multi-sensor fusion will continue to play an important role and bring new applications and breakthroughs in more fields.

2. Robotics Platform Building

2.1. Hardware platform design

The hardware platform of the experimental system of this subject mainly consists of intelligent rubber wheels equipped with intelligent rubber wheels, Raspberry Pi Raspberry Pi-4B, Arduino Mega 2560 control board, DC motors with encoders, LIDAR (RPLIDAR A2M8-R3), SHYDA 720P infrared night vision camera and so on. The 3D design diagram of the robot is shown in Figure 2-1, and the hardware platform with each sensor and the components used are specifically listed in Table 2-1.

The physical drawing of the robot is shown Figure 2-2, the main body of the actuator is assembled with acrylic boards, and four DC motors are used to keep the balance to achieve the robot's walking, the drive system consists of batteries, Arduino electronic control boards, and motor drive modules, and the control system is a Raspberry Pi and a PC computer, and the sensing system adopts an odometer, a LIDAR, and a SHYDA 720P camera, in which the camera needs to scan the obstacles in front of the robot and needs a certain scanning angle, so the SHYDA 720P camera is installed at the head of the robot at a height of 10cm from the ground. The camera needs to scan the obstacles in front of the robot and needs a certain scanning angle, so the SHYDA 720P camera is mounted on the head of the robot, with a height of 10 cm from the ground, and the LIDAR (RPLIDAR A2M8-R3) needs to be close to the robot chassis to obtain the 2D point cloud information of the robot chassis plane, so it is mounted in the middle of the top of the chassis, with a height of 13 cm from the ground. LIDAR (RPLIDAR A2M8-R3) can set the scanning range by algorithm, so the front camera will not affect the scanning result of the single line LIDAR. The robot chassis is a four-wheeled differential chassis. Due to its differential design, the robot chassis has good passability and flexible steering ability, which meets the mobility of the robot in indoor complex and narrow environments.

Table 2-1. Robot Hardware Table

serial number	name (of a thing)	quantities	model number
1	electrical machinery	4	25V JGA370 DC Geared Motor
2	wheel	4	65mm Wheel
3	Raspberry Pi (computer science)	1	Raspberry Pi 4B
4	laser radar	1	RPLIDAR A2M8-R3 LIDAR
5	electronic control panel	1	Arduino Mega 2560 Electronic Control Board
6	rudder	2	SG90 9g Servo
7	Electric Drive Module	1	TB6612 Motor Drive Module
8	Acrylic plate chassis	2	Highly transparent 300mm*300mm*3mm acrylic sheet
9	Infrared night vision camera	1	SHYDA 720P infrared night vision camera
10	power supply	1	Great Wall 100000hmA Charger

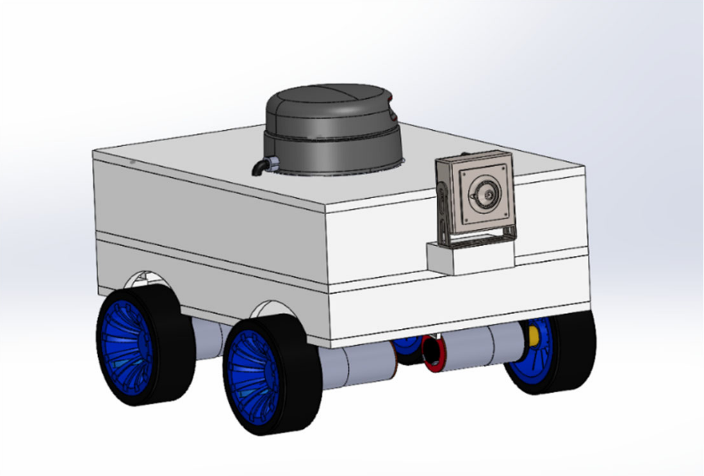


Figure 2-1. Robot 3D design drawing

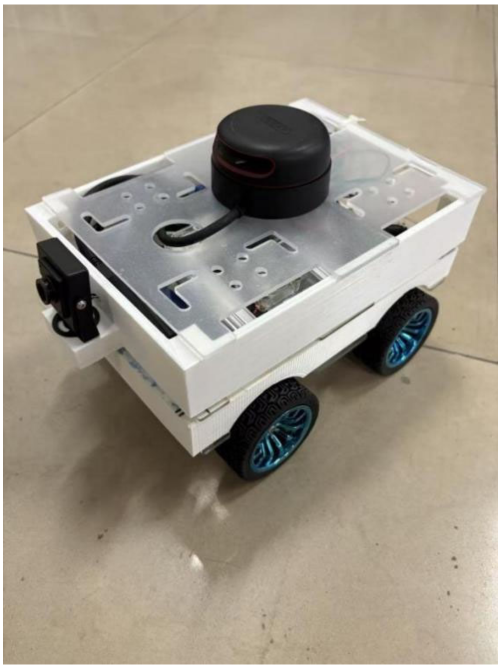


Figure 2-2. Robot Entity

Mechanical structure design: the robot adopts a three-layer structure design, respectively, for the top, middle and bottom layers, of which the bottom layer is a four-wheel all-wheel drive mobile chassis organisation, which has the characteristics of flexible steering, wall adaptability, etc. At the same time, it can also be used in the complex and changeable indoor environment, to avoid the friction generated by the slave wheels to avoid the negative impact on the robot's movement. The middle layer is the controller and various types of sensors, as well as the interconnection between the robot module wiring part, fully play a role in the protection of electronic components, the top layer of the LIDAR mechanism, the mechanism of high flexibility, to facilitate the external PTZ camera real-time shooting of the indoor environment.

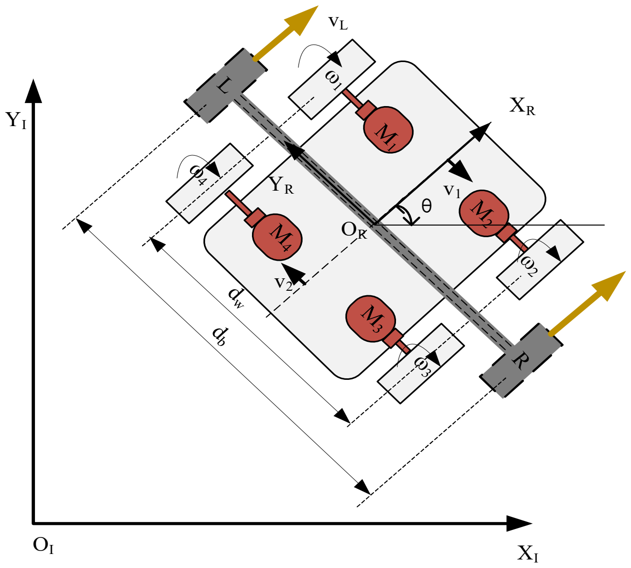


Figure 2-3. Moving chassis kinematics model

In order to facilitate the study, the model is also simplified, as the angular velocity and radius of the wheels on the same side are the same, The angular velocity of the left side is$\omega_L = \omega_1 = \omega_4$,and the angular velocity of the right side is$\omega_R = \omega_2 = \omega_3$, and the grey and white solid line four-wheel differential model in Fig. 2-3 is equated to the dark grey dashed line two-wheel differential model. The positions of the equivalent left and right wheels are L and R, respectively, and the equivalent distance between the centre lines of the two wheelsd_b is, since it is assumed that there is no slip in this model,$d_b = d_w$. The linear velocities of the two wheels are:

$$\begin{cases} \mathcal{V}_L = \omega_L \cdot r \\ \mathcal{V}_R = \omega_R \cdot r \end{cases}$$

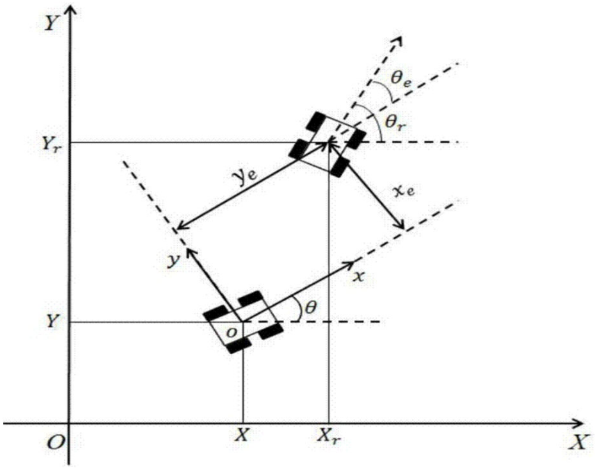


Figure 2-4. Trajectory of the trolley

As shown in Figure 2-4, let the robot forward direction beχ axis andγ axis positive direction, the robot motion time interval isΔt , the robot speed ,$\mathcal{V}_x \mathcal{V}_y$ and angular velocityω , through the ,$\mathcal{V}_x \mathcal{V}_{y,} \omega$ and integration under the interval time, we can get the displacement of the robot in the coordinate system χ_e, γ_e *and* yaw angle θ_e . From this, the motion model of the robot located in the 3D world from moment t to moment t + 1 is derived:

$$\begin{bmatrix} \chi_{t+1} \\ \gamma_{t+1} \\ \theta_{t+1} \end{bmatrix} = \begin{bmatrix} \chi_t \\ \gamma_t \\ \theta_t \end{bmatrix} + \begin{bmatrix} \cos\theta_t & -\sin\theta_t & 0 \\ \sin\theta_t & \cos\theta_t & 0 \\ 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} \chi_e \\ \gamma_e \\ \theta_e \end{bmatrix}$$

2.2. Software Platform Design

The robot software system is mainly configured as a Linux-based virtual machine on the remote computer, i.e. PC, which uses Ubuntu 20.04 system, and the robot Raspberry Pi is installed with ROS melodic version of Ubuntu 18.04 system. The ROS systems of the robot and the remote computer were configured in a master-slave configuration, with the robot as the host, and the two communicated with each other via SSH under the LAN to achieve motion control and real-time monitoring of the robot by the remote computer. The mobile robot consists of a high-speed processing layer and a real-time control layer, and the high-speed processing layer and the real-time control layer use asynchronous serial communication; the high-speed processing layer contains a Raspberry Pi, a deep degree camera, a LiDAR, and a keypad operation. Through SSH remote control to achieve the link system ROS Melodic to build a distributed communication architecture, using the unique multi-machine distributed communication function of the ROS system to configure the network communication environment between the robot and the PC with a LAN, and at the same time configure the SSH master and slave, with the Raspberry Pi as the master and the PC as the slave. Through SSH remote connection, "PC + Embedded" is realised, i.e. the embedded system (Raspberry Pi) acts as the control system of the robot body for data acquisition and direct chassis control, while the PC end realises remote monitoring and manipulation to achieve graphical display and function calculation.

The PC side uses ROS for the robot system construction and sensor space-time synchronisation module, and the Raspberry Pi uses the ROS workspace in the Linux system. The Raspberry Pi is mainly responsible for issuing movement commands to the real-time control layer and receiving status information returned by the robot's real-time control layer, as well as the sensor data such as the depth camera and LiDAR. The overall system results of the robot are shown in Figure 2-5.

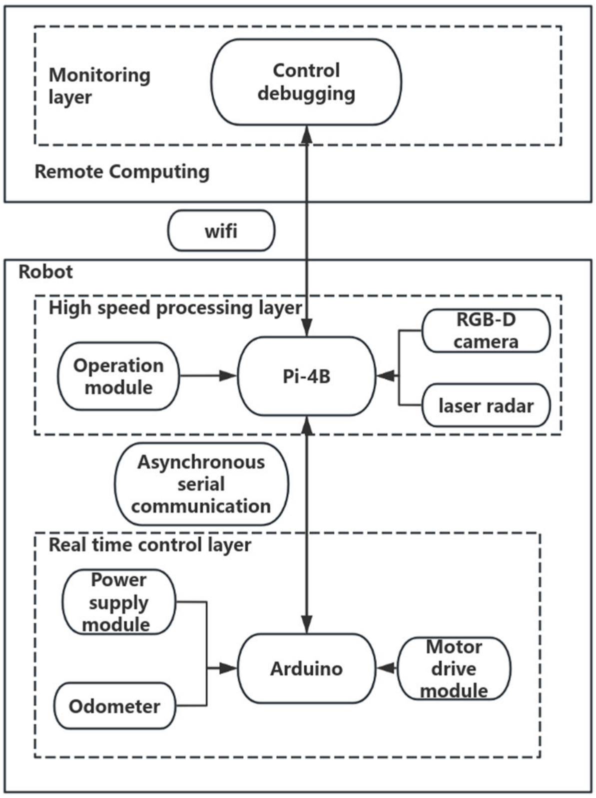


Figure 2-5. Overall structure of the robot system

3. Data Processing and Multi-Sensor Fusion Strategies

3.1. Data processing

Wheel odometer data processing is the basis of robot movement, firstly reading the encoder pulses each motor encoder outputs a pulse signal indicating the rotation of the wheel. The following calculation formula can be used:

$$\theta = \frac{N_{pulse}}{N_{rev}} 2\pi$$

Whereθ is the current radian of wheel rotation;N_{pulse} is the number of pulses read by the encoder;N_{rev} is the number of pulses per revolution of the encoder.

The number of encoder pulses is read through the Arduino's external interrupt function and accumulated to calculate the angle of rotation. Calculating the wheel linear velocity Calculates the linear velocity based on the angular velocity of the wheelω :

$$V_{wheel} = R\omega$$

Where R is the wheel radius;ω is the angular velocity, calculated as:

$$\omega = \frac{\theta}{\Delta t}$$

whereΔt is the sampling interval.

After calculating the X, Y velocity and angular velocity, the Arduino electronic control board sends the data to the Raspberry Pi through the serial port (UART). The Raspberry Pi parses this data through rosserial and publishes a ROS Odometry message: ultimately, /odom topic provides information about the robot's position for use in SLAM and path planning.

Secondly, facing the processing of LiDAR data, SLAM through the use of LiDAR sensors is called laser SLAM technology, after a comparison of the various laser SLAM algorithms, the robot adopts the Gmapping algorithm as the basic algorithm for experimentation and research, based on the particle filtering framework of the laser SLAM, RBpf particle filtering algorithms, i.e., to separate the process of localisation and map building, localisation is carried out first, and then map building. and then build the map, combined with odometry and laser information, each particle carries a map, and the construction of small scene maps requires less computation and higher accuracy.The core problem of Gmapping is to build the environment around the robot while completing the robot's own localisation, which can be described by the joint distribution model in the probability theory.At the current moment the robot's sensor data$\mathrm{Z}$ and the robot's Under the premise of the sensor data of the robot$m$ and the control parameter$\mathcal{U}$ at the current moment, the robot position$\mathcal{X}$ and the map of the environment in which the robot itself is located can be expressed by the following equation:

$$\mathcal{P}(\mathcal{X}_t, m|\mathrm{Z}_{1:t}, \mathcal{U}_{1:t-1})$$

Based on the Bayes' Rule of probability theory, the following equation can be derived:

$$\mathcal{P}(\mathcal{X}_t, m|\mathrm{Z}_{1:t}, \mathcal{U}_{1:t-1}) = \mathcal{P}(m|\mathcal{X}_{1:t}, \mathrm{Z}_{1:t})\mathcal{P}(\mathcal{X}_{1:t}|\mathrm{Z}_{1:t}, \mathcal{U}_{1:t-1})$$

Finally processing camera data, the robot uses depthimage_to_laserscan can be achieved depth image and radar data conversion, radar data is two-dimensional, planar, depth image is three-dimensional, is a number of two-dimensional (horizontal) data vertical superposition, if the three-dimensional data will be converted to two-dimensional data, only need to take the depth map of the a layer can be. The visual SLAM front-end estimation, i.e., the front-end data processing of the RGB-D camera, is mainly based on feature comparison and matching between neighbouring image frames to compute the pose transformation. In the multi-sensor fusion SLAM scheme proposed in this project, the RGB-D camera is able to capture both the RGB image and the depth image of the object to be measured, and the RGB image is firstly subjected to feature matching, and then the changes between adjacent images are obtained to get the camera's pose changes, which, combined with the depth information of the obstacles scanned by the robot, can be used to estimate the robot's own motion state and motion pose. Figure 3-1 shows the specific framework of RGB-D camera front-end data processing.

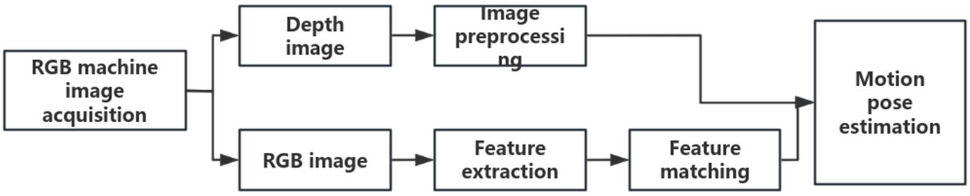


Figure 3-1. RGB-D Camera Front-End Data Processing Framework

3.2. Multi-sensor fusion strategy

3.2.1. Fusion of LiDAR and odometer data

To solve the problem of time synchronisation and spatial calibration of LiDAR and odometer. The LiDAR and wheeled odometer (50Hz) are aligned with time stamps using linear interpolation to ensure that the time deviation of the data is less than 5 ms. Using the Eye-on-Hand calibration method, the data is collected by the robot through a uniform linear motion to calibrate the positional transition relationship between the LiDAR and the wheeled odometer to eliminate the installation offset error. The LiDAR generates 2D point cloud data through rotational scanning to provide accurate distance measurements of the environment, while the odometer data provides position and velocity information of the robot during motion. The fusion of the two data can be achieved through ROS topic communication. The LiDAR data is transmitted as ROS message format LaserScan, which transmits the distance information of the environment to the host computer through the scan topic. Odometer data is transmitted as Odometry messages containing the robot's motion status (speed, position, etc.) via odom topics. The topic transmits the LiDAR and odometry data is processed to compute the exact position of the robot which in turn is used for SLAM and path planning. Meanwhile the TF coordinate transformation of the robot is as follows:

Table 3-1. TF transformations for Gmapping

TF transformation		descriptions
Mandatory transformations	<scan frame>→ base_link	Transformations between the LiDAR coordinate system and the base coordinate system, typically published by robot_state_publisher or static_transform_publisher
	base_link→ odom	Transformations between the base coordinate system and the odometer coordinate system are generally issued by the odometer node
Transformation of releases	map→ odom	Transformation between the map coordinate system and the robot's odometer coordinate system to estimate the robot's position in the map

After having started the cart and sensors, released tf, odom, scan, start the gmapping algorithm its TF tree is shown below

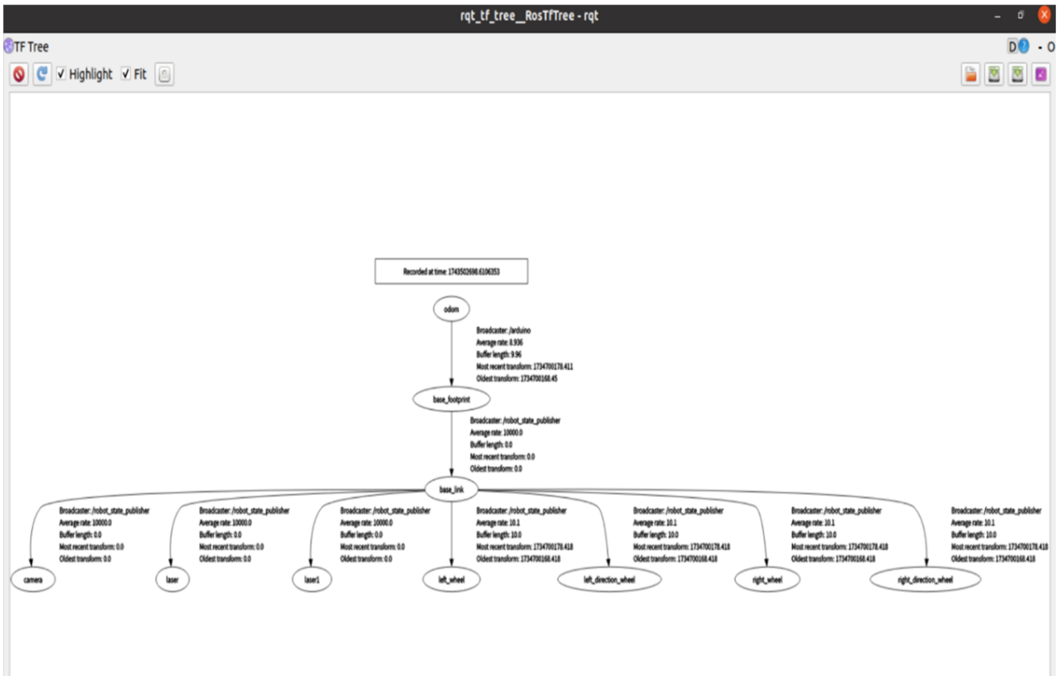


Figure 3-2. TF Tree

An improved mean square information filtering (MSIF) algorithm is proposed to address the drift and cumulative error of the wheeled odometer.

The system state vector is the robot position $\chi = [\mathcal{X},\mathcal{Y},\mathcal{Z}]^T$, the inputs are the wheeled odometer linear velocity$v$ andω angular velocity, and the LiDAR provides the angular velocity$\dot{\omega}$ and acceleration a. The system state vector is the robot position , and the inputs are the wheeled odometer linear velocity and angular velocity.

The state prediction equation is:

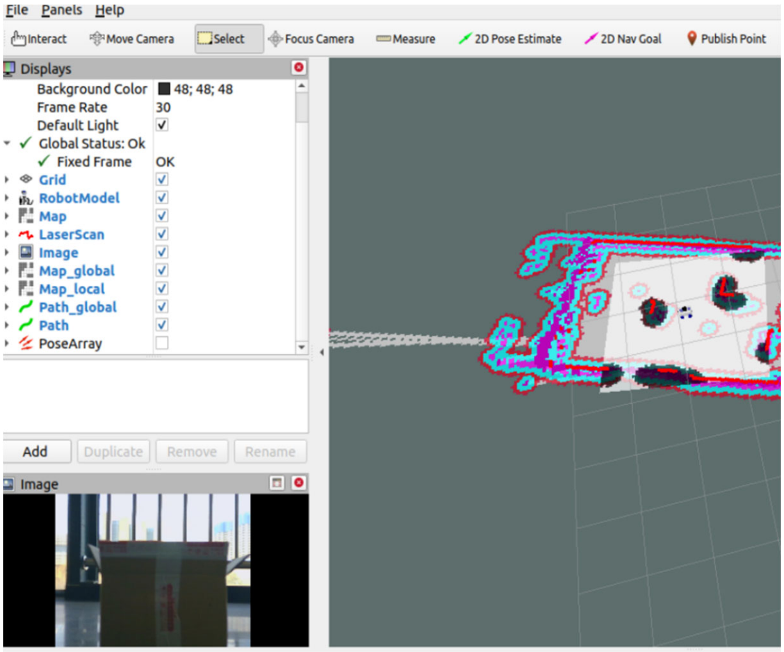
$$\chi_{\kappa|\kappa-1} = \chi_{\kappa-1} + \begin{bmatrix} v\Delta t\cos\theta \\ v\Delta t\sin\theta \\ \omega\Delta t \end{bmatrix} + w_{\kappa}$$

wherew_{κ} is the process noise and follows a Gaussian distribution.

The residual difference between the angular velocity and the wheel odometer angular velocity is$z_{\kappa} = \omega - \dot{\omega}$, which is fused by Kalman gain-weighted fusion to suppress the high-frequency noise and low-frequency drift. The angular velocity error is reduced by 42% after fusion.

3.2.2. Fusion of RGB camera data with LiDAR data

RGB cameras provide visual information to the robot that helps to identify obstacles or feature points in complex environments. Although RGB cameras do not provide positional information directly, they can complement environmental features such as colours or textures that LiDAR cannot sense in some cases. image_transport library in ROS can be used to transfer image data, transferring RGB image information via the image_raw topic. The robot analyses the images using obstacle detection and feature extraction. In order to achieve the data fusion between the RGB-D camera and LIDAR, a vertical projection and feature matching strategy is proposed.Firstly, 3D point cloud compression is used to project the 3D point cloud of the RGB-D camera to the scanning plane of the LIDAR (height ±5cm), and the horizontal layer of the point cloud is extracted, retaining the effective distance (0.5m-10m). Secondly, the extracted data are subjected to feature enhancement, the linear features in the LiDAR data are extracted by the RANSAC algorithm, the key points are extracted based on the ORB feature detector, and the RGB-D data are combined with the depth information to generate local feature descriptors. Finally, the two types of features are matched in both directions, and the mis-matched points are eliminated (threshold: Euclidean distance < 0.1m), and finally the fused point cloud map is generated. As shown in Figure 3-3.



Background Color ■ 48; 48; 48
Frame Rate 30
Default Light ☑
✓ Global Status: Ok
✓ Fixed Frame OK
Grid ☑
RobotModel ☑
Map ☑
LaserScan ☑
Image ☑
Map_global ☑
Map_local ☑
Path_global ☑
Path ☑
PoseArray ☐

Figure 3-3. Fusion point cloud map

3.2.3. iRTAB-Map Algorithm Fusion Mapping Study

Multi-sensor fusion for robots is mainly to optimise the initiation of chassis, radar and camera related nodes and to achieve the association of robot chassis with odometry, radar and camera through coordinate transformation. Aiming at the problems of large errors in localisation and mapping, low localisation accuracy and poor system robustness of mobile robots using a single sensor in unknown environments, a multi-sensor fusion mapping scheme based on LIDAR, RGB-D camera and wheel odometers is constructed by combining with the sensor data processed in the previous section. Firstly, the wheel odometers are fused using the mean square information filtering algorithm to reduce the drift error and improve the robot's own positioning accuracy. Secondly, the regional image fusion algorithm fuses the 3D point cloud, object colour, distance and other visual information acquired by the RGB-D camera into the 2D laser data to make up for the defects of the single-wire LiDAR that cannot perceive the spatial structure, so as to improve the completeness of the robot's mapping and the accuracy of its own localisation. Then, the iRTAB-Map algorithm fuses the multi-sensors to build a map. Finally, the multi-sensor fusion mapping experiment is carried out in a simulated complex indoor environment, and the multi-sensor fusion mapping algorithm is applied in the experiment to verify the completeness of the mapping and the accuracy of the positioning.

Aiming at the problem of how to fuse the data acquired by different sensors and build a map, this paper proposes a multi-sensor fusion SLAM scheme based on a single-wire LiDAR, an RGB-D camera, and a wheel odometer, and the block diagram of the fusion scheme is shown in Figs. 3-4. Firstly, the wheel odometer is used to output the position and motion trajectory of the robot with high efficiency and low error, is used as the initial position of the robot and the data source for the position correction during the subsequent motion. After that, the depth camera and LiDAR are fused using the area image algorithm, the depth image acquired by the depth camera is converted into a 3D point cloud, which is then compressed to the same scanning level as the single-line LiDAR and projected to obtain the 2D laser data, which is then matched with the LiDAR data for the point cloud, and then the multi-sensor data are fused using the iRTAB-Map algorithm and the maps are constructed.

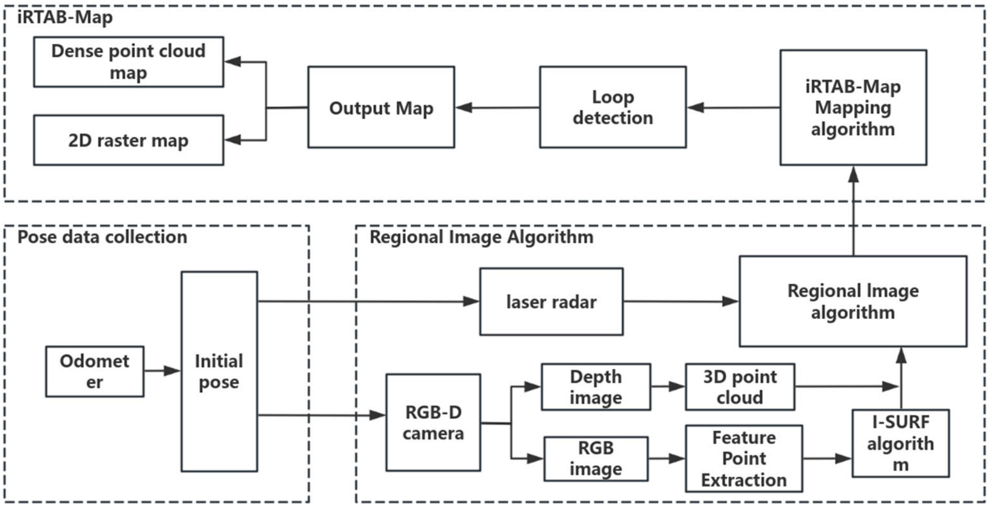
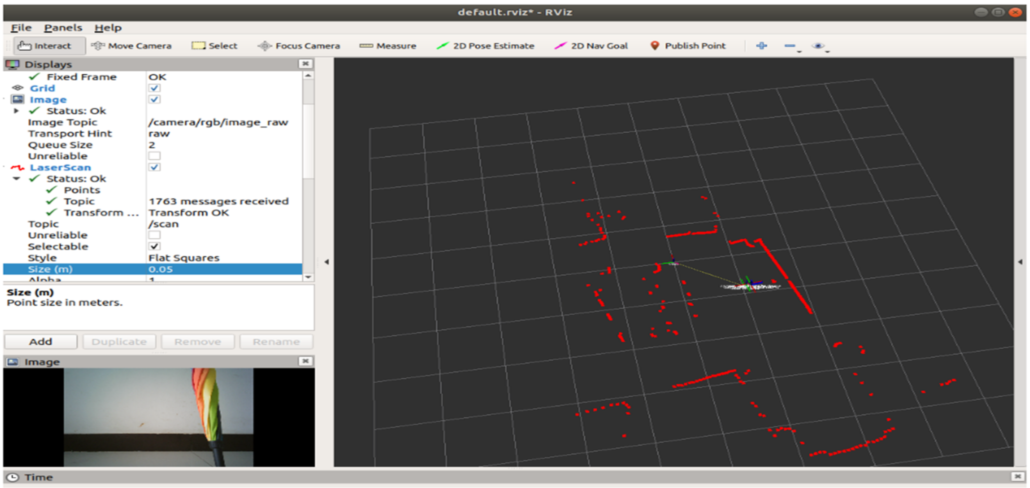


Figure 3-4. Multi-sensor fusion mapping scheme

The robot uses the iRTAB-Map algorithm to integrate the sensor pre-processing data obtained in the previous section and the fused data from a single LiDAR and RGB camera sensor for the study of fusion map building algorithms. iRTAB-Map algorithm is based on two basic algorithms, loopback detection and map optimisation. iRTAB-Map algorithm provides a highly efficient memory management scheme in order to satisfy the requirements of real-time performance and it can subscribe to multiple sensor information simultaneously to perform loopback detection and update the environment map in real-time. To meet the real-time requirements, the iRTAB-Map algorithm provides an efficient memory management scheme and subscribes to multiple sensors at the same time for loopback detection and real-time update of the environment map. The system uses visual frames, which are extracted by the I-SURF algorithm from an RGB image obtained from , and through this process, location information associated with the image is generated. iRTAB-Map algorithm uses bag-of-words to save these visual frames in a visual library for comparing previously accessed locations for closure detection. The system uses KD trees for comparison and retrieval to improve performance speed. Since loop detection is possible within maps, it is also possible to find loop detection between different maps due to the multi-subscription topic property of the system. After successful detection of closed loops, 3D transformations are applied to the matched images using the RANSAC method. iRTAB-Map is a graph-based SLAM system that uses locations as nodes. There are two different types of links between nodes: neighbourhood links and loopback links. Neighbourhood links are links between two consecutive positions; if a closed loop is detected between two related positions then the two positions are connected together, called a loopback link. After adding the loopback links, the map is optimised using the Tree-based network Optimizer (TORO) method to reduce the ranging error. Finally, the dense point cloud map and 2D raster environment map are output through the data from each sensor after fusion. As shown in Figure 3-5.



✓ Fixed Frame	OK
Grid	☑
Image	☑
✓ Status: Ok	
Image Topic	/camera/rgb/image_raw
Transport Hint	raw
Queue Size	2
Unreliable	☐
LaserScan	☑
✓ Status: Ok	
✓ Points	
✓ Topic	1763 messages received
✓ Transform ...	Transform OK
Topic	/scan
Unreliable	☐
Selectable	☑
Style	Flat Squares
Size (m)	0.05
Alpha	1

Size (m)
Point size in meters.

Figure 3-5. 2D Raster Environment Map

4. Mapping Experiment

4.1. Experiments and analysis of results

4.1.1. experimental environment

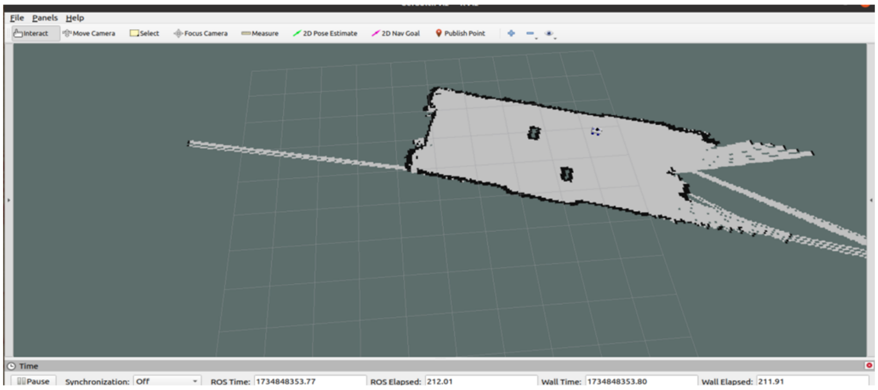
In order to simulate variable indoor complex environments, the experimental environment was idealised in the multi-sensor fusion robot mapping experiments Ideal environment: 5m×5m simulated post-disaster scene containing cubic obstacles. Real environment: floor corridor and other complex structures as shown in Figure 4-1. At the same time, the ideal indoor environment has a single lighting condition and the floor is easy to be slippery, simulating the scene of slippery indoor floor caused by the complex situation, and the distance between each obstacle is small, to restore the narrow terrain that the robot needs to pass through in the real environment, and to test the robot's passability.

Figure 4-1. Experimental simulation environment

4.1.2. Navigation and map building performance experiments

In order to validate the multi-sensor fusion mapping technique in this project, two multi-sensor fusion mapping comparison experiments are set up, the first one is a single LiDAR mapping experiment, which uses the gampping algorithm to construct an environment map of the ideal indoor environment. The second is a multi-sensor fusion mapping experiment to compare the results. The proposed fused data from each sensor is used as input to build an environment map based on the iRTAB-Map algorithm, and a dense point cloud map and a 2D raster environment map are output from the fused data from each sensor.

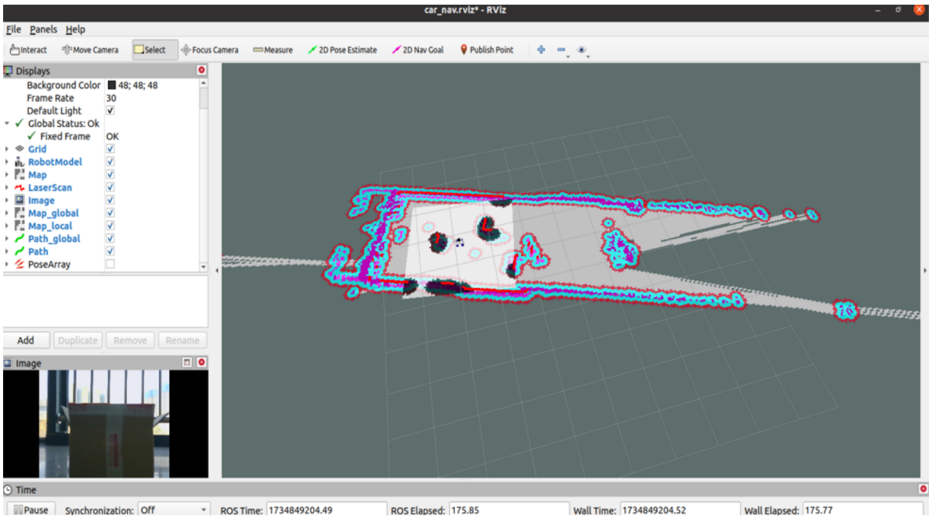
Firstly, the single LIDAR is experimented in the simulated variable indoor complex environment for map building experiments, and the results are shown in Fig. 4-2. Under the realistic conditions of three obstacles in the real environment, only two obstacles of larger size are identified in the results of the single LIDAR map building experiments.



Synchronization: Off
ROS Time: 1734848353.77
ROS Elapsed: 212.01
Wall Time: 1734848353.80
Wall Elapsed: 211.91

Figure 4-2. Single LiDAR map building results

The second experiment experiments more using sensor fusion to build a map, using multi-sensor fusion robot can fusion system in the two-dimensional map clearly present dynamic obstacle contours will be all the obstacles are recognised, and real-time release of image information and obstacle detection. Two-dimensional LiDAR and RGB-D camera two sensors coordinate system and time for unification; to obtain the relative position relationship, through the two sensors were acquired through the environmental information, to obtain two-dimensional laser point cloud data and three-dimensional point cloud data; through the regional image algorithm will be the depth of three-dimensional image data and two-dimensional laser point cloud data for fusion. The experimental results are shown in Figure 4-3.



Background Color 48; 48; 48
Frame Rate 30
Default Light ✓
✓ Global Status: Ok
✓ Fixed Frame OK
Grid ✓
RobotModel ✓
Map ✓
LaserScan ✓
Image ✓
Map_global ✓
Map_local ✓
Path_global ✓
Path ✓
PoseArray ☐

Synchronization: Off
ROS Time: 1734849204.49
ROS Elapsed: 175.85
Wall Time: 1734849204.52
Wall Elapsed: 175.77

Figure 4-3. Multi-sensor fusion map building

4.1.3. Experimental results of building maps for multi-sensor fusion

Comparison and experimental analysis of single-sensor and multi-sensor fusion are carried out in terms of mapping effect and positioning accuracy, and the experimental results prove that the multi-sensor fusion scheme is better than the single-sensor mapping scheme in terms of mapping effect and positioning accuracy, and its mapping accuracy and positioning accuracy in complex indoor environments satisfy the accuracy requirements of robots in complex environments. Comparing the cumulative errors of positioning in complex indoor environments of multi-sensor fusion, single laser, and single camera, it can be concluded that both multi-sensor fusion scheme and single LIDAR scheme have lower cumulative errors of positioning than RGB-D camera, which is caused by the fact that in complex indoor environments, the RGB-D camera has the highest amount of data collection and the largest amount of computation, and the inaccuracy of the location of the point cloud may arise in the process of computation and other phenomena that increase the error, so the cumulative error will be larger than the cumulative error of positioning after LIDAR and multi-sensor fusion. From the experiment, it is concluded that the cumulative error of positioning of multi-sensor fusion is smaller than that of single laser and smaller than that of single camera, because single LIDAR and single camera are not fused with wheel odometer data in the positioning experiments, so there will be a drift phenomenon, which results in a larger error, while multiple sensors in the multi-sensor fusion scheme can complement each other's information so the cumulative error is minimal, which results in the cumulative error of the multi-sensor fusion scheme in the complex indoor environments is higher than that of a single sensor. The raster map accuracy of complex indoor rescue robots is generally 5-10 cm, and the positioning accuracy is 2-10 cm. Through the experiment, it can be seen that the robot's navigation accuracy is high and it can observe the image information of obstacles and road conditions in real time through the camera, and the experimental results also verified that the multi-sensor fusion algorithm has good obstacle avoidance ability even in the face of dynamic obstacles, which further proves the feasibility of the multi-sensor fusion algorithm and meets the requirements of complex indoor environments. This further proves the feasibility of the multi-sensor fusion algorithm to meet the complex and changing different indoor environments.

5. Conclusions and Outlook

Based on the multi-sensor fusion technology, this study designs a multi-sensor fusion robot including a single-wire LiDAR sensor, an RGB-D camera, and a wheel odometer, based on which the robot achieves the functions of acquiring real-time environmental data in unfamiliar and constructing maps of complex environments, and then experimentally verifies the proposed multi-sensor fusion scheme for map construction. By improving the data processing algorithm and fusion strategy, the accuracy and robustness of complex indoor environment mapping are significantly improved. From the significance level, it has far-reaching social value and scientific and technological exploration value. At the social level, it is expected to provide reliable travelling assistance for the visually impaired, reduce their dependence on traditional blind guides, and greatly enhance the mobility and quality of life of the visually impaired group; in the industrial field, it is able to undertake repetitive and dangerous tasks, such as inspections in hazardous environments and material handling in logistics and warehousing, which will reduce manpower costs and ensure personnel safety at the same time. From the perspective of scientific and technological exploration, this project promotes the cross-fertilisation of multiple disciplines, closely integrating robotics, sensor technology, computer science, artificial intelligence and other disciplines, providing new ideas and practical cases for academic research in related fields, and promoting the further development of the discipline.

The robot builds a system framework based on ROS, making full use of its advantages of open source, modularity and expandability, which provides strong support for the efficient collaboration of the robot's modules. The data from different sensors complement each other, enabling the robot to perceive the surrounding environment in an all-round and high-precision way, which greatly improves the accuracy and reliability of environmental cognition. The robot can quickly plan a reasonable path in a complex dynamic environment, make real-time decisions and adjustments according to environmental changes, effectively avoid obstacles, and achieve stable and efficient autonomous navigation. In indoor scenarios, whether in large shopping malls and office buildings with complex structures, or in family environments with diverse layouts, the robot can quickly build maps to achieve accurate positioning and navigation, which can be applied to indoor cleaning, logistics and distribution, and companion services and other fields.

In addition, in some special environments, such as warehouses and factories, robots are capable of handling materials and inspecting equipment, showing good adaptability to the environment and the ability to perform tasks. With its advanced technology, reliable performance and wide range of applications, this work is well suited to the market demand. If it is further optimised in terms of cost control and product stability, and then mass-produced and marketed, it is expected to trigger changes in many industries and create great economic and social benefits. Future work will focus on dynamic obstacle processing and embedded platform optimisation to further improve system real-time performance.

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