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Design and Implementation of Efficient SLAM System Based on Multi-Sensor Fusion

Shaohui Wang [*], Fei Li

School of Information Technology and Engineering, Shenyang University of Technology, Shenyang 110000, China

[*] **Corresponding author**: wangshaohui9910@163.com

Abstract: In Simultaneous Localization and Mapping (SLAM) algorithms, the robustness of single sensors is relatively poor. To address this issue, this study develops a multi-sensor fusion platform that integrates data from LiDAR, stereo cameras, and IMUs, and employs advanced algorithms such as ORB-SLAM2 and Cartographer for efficient data processing and map construction. For point cloud data, we apply the Iterative Closest Point (ICP) algorithm for point-to-point optimization, effectively solving the issue of large map accumulation errors in traditional LiDAR-based SLAM algorithms, which rely solely on odometry for estimating the robot's pose. By using publicly available datasets and conducting multiple map construction experiments in a real campus environment, the proposed method's effectiveness and feasibility are validated, significantly reducing error accumulation and producing more accurate localization and map construction results.

Keywords: Multi-sensor fusion, SLAM technology, ICP algorithm, Mobile robot, Stereo camera, LiDAR.

1. Introduction

With the rapid development of science and technology, mobile robots are more and more widely used in modern life and industry, especially in automatic driving, industrial robots, unmanned aerial vehicles and other fields. In order to achieve efficient and accurate autonomous navigation and task execution, the localization and mapping technology of mobile robots becomes crucial. Simultaneous Localization and Mapping (SLAM) technology enables robots to accurately locate their own position while sensing and building an environmental map through sensors in an unknown environment, to realize autonomous navigation and decision-making [1, 2]. The wide application of SLAM technology has profoundly changed many fields, especially in autonomous driving, SLAM can provide accurate positioning and path planning for vehicles [3]. In industrial robots, SLAM helps robots perform tasks autonomously in complex production environments [4]. In the field of Uavs, SLAM technology enables Uavs to fly safely in unknown or unstable environments with GPS signals [5]. According to the different types of main sensors, researchers mainly divide SLAM technology into two categories: visual SLAM and laser SLAM [6].

Visual SLAM uses the camera as the main sensor, and realizes the construction and expression of the surrounding environment by analyzing and processing the images collected by the camera [7]. However, when there is a lack of reliable and stable lighting conditions in the environment, the robustness of visual SLAM mapping will be greatly reduced [8]. Multi-sensor fusion technology has shown great potential in improving the performance of SLAM systems. By combining information from multiple sensors such as vision, LiDAR, and IMU, the deficiency of a single sensor can be remedied [9, 10]. For example, IMUs can provide high-frequency dynamic information to help compensate for the shortcomings of vision and LiDAR in highly dynamic scenes. LiDAR provides accurate 3D environmental data and ADAPTS to different lighting conditions. However, visual sensors have obvious advantages in detail perception. With effective data fusion, SLAM systems can provide higher accuracy and robustness in more complex and dynamic environments. In order to effectively solve the problems of low positioning accuracy and incomplete obstacle recognition of simultaneous localization and map construction of single sensor, and improve the reliability of SLAM navigation and positioning of autonomous vehicles, it is particularly important to adopt multi-sensor fusion [11]. Common multi-sensor fusion methods include multi-line lidar and millimeter-wave radar data fusion, infrared sensor and visible sensor fusion, etc. [12, 13]. The main research goal of this study is to propose a new multi-sensor fusion technology based on the algorithm of ORB-SLAM2 [14, 15] and Cartographer [16], and to design and implement a mobile robot localization and map building system. The system fuses IMU [17], LiDAR [18], and binocular cameras [19, 20], and solves technical problems such as sensor data synchronization, spatial registration, and algorithm optimization. Specifically, the system will use an adaptive time synchronization method to ensure the effective alignment of different sensor data. The optimized ICP (Iterative Closest Point) algorithm is used to register the point clouds, to improve the accuracy and robustness of data fusion. In addition, an adaptive weighting strategy is proposed to dynamically adjust the fusion weight of sensor data according to the reliability of different sensors to improve the performance of the system in complex environments.

2. Multi-Sensor Fusion

In the whole system, each sensor works independently and asynchronously. The sampling rates are not all the same. The primary fusion (preprocessing) of each platform is performed in its own reference coordinate system and each platform provides reports to the fusion center asynchronously. Therefore, it is necessary to perform temporal and spatial registration before fusion to form a unified observation point in time and space.

In the SLAM system, how to effectively fuse the data of multiple sensors such as vision, LiDAR and IMU is the key to improve the robustness and accuracy of the system. Multi-sensor fusion techniques [21, 22] can effectively improve the accuracy of localization and mapping by exploiting the complementary characteristics of different sensors, especially in complex and dynamic environments. Traditional single-sensor SLAM systems rely on a single sensor (such as vision, lidar or IMU) to complete the map construction and localization tasks. However, due to the limitations of a single sensor (such as vision failure in low light, lidar on transparent objects or reflective surfaces, etc.), their applications are limited. Therefore, the combination of data from multiple sensors can compensate for the shortcomings of a single sensor, thus improving the robustness and accuracy of the system. IMU can provide high-frequency dynamic information to provide the robot with position and velocity estimation during motion, while LiDAR complements visual information with accurate 3D spatial information to make up for the lack of depth perception in visual SLAM. The design of the adaptive sensor fusion framework focuses on dynamically adjusting the weight allocation of each sensor in the SLAM system according to the reliability of different sensors. This framework can effectively deal with the challenges of sensor failures, occlusions or environmental changes in multi-sensor environments.

2.1. Time Alignment Optimization

In SLAM systems with multi-sensor fusion, different sensors usually have different sampling frequencies in time, and there are problems such as clock skew, delay or synchronization error. Therefore, accurately aligning the data of different sensors is the key to ensure effective fusion and accurate positioning of the system.

In multisensor systems, sensors usually collect data at different time steps. The task of time registration is to synchronize the different measurements about the same target to the same reference time scale. For different sensors and different platforms, their measurements of the target are independent of each other, the time they report to the fusion center is independent of each other, and the time required to transmit information between each sensor and the fusion center is also different, so there may be time differences between the reports of each sensor. Therefore, the asynchronous information should be registered to the information at the fusion time before fusion [23].

2.2. Optimization of Spatial Registration

In the multi-sensor fusion SLAM system, spatial registration optimization is a key step to ensure that different sensor data can be accurately aligned. Especially when combining vision, LiDAR, and IMU data, accurate calibration of extrinsic parameters (i.e., relative position and pose between different sensors) is critical. The accuracy of external parameter calibration directly affects the positioning accuracy and map construction effect of the whole system. For the sensor fusion process in ORB-SLAM2 and Cartographer algorithm, the optimization of external parameter calibration and spatial registration is particularly important.

The ORB-SLAM2 algorithm relies on efficient image feature matching and localization techniques, and its effect is greatly affected by the accuracy of extrinsic parameter calibration between the camera and the IMU. Accurate external parameter calibration can ensure that the high-frequency dynamic information of the IMU is correctly aligned with the visual data, thereby improving the overall accuracy and robustness of the SLAM system. Traditional external parameter calibration methods are usually completed by manual measurement or calibration tools in static environments. However, this method cannot adapt to the changes of dynamic environments and the continuous migration of sensors [25].

2.3. Calibration of External Parameters

In order to solve the above problems, the online calibration optimization method is proposed and applied to the multi-sensor fusion system. This method fine-tunes and optimizes external parameter calibration parameters through real-time data feedback and error analysis [24]. In practice, by adjusting the calibration values of the external parameters several times, combined with the data stream of the sensor, the real-time calibration optimization can be realized in a dynamic environment. For example, through the gradual correction in the process of environmental changes, the system can adaptively optimize the extrinsic calibration parameters, thereby improving the accuracy of spatial registration and the stability of the system.

In the Cartographer algorithm, spatial registration optimization similarly relies on accurate calibration of the sensor extrinsic parameters. The Cartographer realizes the effective fusion of sensor data through the graph optimization method, and the optimization effect depends on the accurate relative pose estimation between sensors such as LiDAR and IMU. The online calibration optimization method can automatically correct the external parameter calibration in each scan or data fusion process, to effectively reduce the long-term drift problem caused by the initial calibration error and improve the map construction accuracy of the system.

2.4. Adaptive Weighting Strategy and Fusion Optimization

In the process of multi-sensor fusion, the performance difference of different sensors may lead to the instability of fusion results. Therefore, designing an appropriate adaptive weighting strategy is the key to optimize the effect of sensor fusion [25]. The adaptive weighting strategy dynamically adjusts the weight of each sensor in the process of data fusion according to the performance of the sensor and the change of the environment, to ensure that the system can optimally use the data of each sensor according to the actual situation.

The design of the adaptive weighting strategy is based on the evaluation of the confidence and reliability of the sensor [26]. In practice, the performance of different sensors varies greatly in different environments. For example, vision sensors can provide high-quality localization and mapping data in well-lit and clear texture environments, but may perform poorly in scenes with low lighting or complex environments. The dynamic information provided by IMU has a high frequency, which can provide accurate pose estimation in dynamic scenes, but it is greatly affected by error accumulation in long-term use.

Therefore, the confidence of a sensor needs to be dynamically adjusted based on its measurement accuracy and signal quality as well as environmental conditions. For example, in low light conditions, the confidence of a vision sensor can be reduced and the confidence of a LiDAR or IMU can be increased accordingly. By dynamically adjusting the weights of sensors in the graph optimization process, the system can give priority to the most reliable data sources, thus improving the localization accuracy and map quality.

In addition, the evaluation of sensor reliability is equally important. In case of sensor failure or abnormal data, the fusion system needs to be able to automatically reduce the weight of this sensor and compensate with data from other sensors. For example, in some scenarios, lidar data may be affected by reflective surfaces or transparent objects, resulting in large measurement errors, at which time the weight of IMU and visual data will be appropriately upgraded to ensure the robustness of the system.

By designing such an adaptive weighting strategy, the problem of unbalanced sensor performance in dynamic environments can be effectively solved, the accuracy and robustness of SLAM system can be improved, and efficient data fusion can be achieved in different environments.

2.5. Point Cloud Registration

The ICP (Iterative Closest Point) algorithm, shown in Figure 1, is a widely used method in point cloud registration that aims to minimize the error between the source point cloud and the target point cloud through an iterative process. The basic principle of ICP algorithm is to calculate the transformation matrix between the source point cloud and the target point cloud by finding the nearest neighbor point of each source point cloud, then apply the transformation to update the source point cloud, and repeat the process until the error converges.

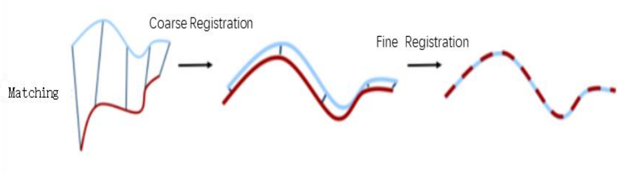

Figure 1. ICP algorithm flow

In multi-sensor point cloud registration, the difference of data density requires the weighting of different sensor data, and the adaptive weighting algorithm is used to optimize the data fusion process. By density weighting and spatial distribution optimization, it can improve the contribution of different sensor data in the registration and optimization process.

$$R^*, t^* = arg\min_{R,t} \frac{1}{|P_s|}\sum_{i=1}^{|Ps|} \| p_t^i - (R \cdot p_s^i + t) \|^2 \qquad (2\text{-}1)$$

Where, P_s denotes the number of closest point pairs; P_s And P_t denote the points in the source point cloud and the target point cloud in one-to-one correspondence respectively; R and t denote rotation and translation, which are the parameter variables of the iteration. For the above formula, using the SVD decomposition method, let H be a 3*3 matrix, as shown in the formula:

$$H = \sum_{i=1}^{|Ps|} (p_s^i - \overline{p}_s)(p_t^i - \overline{p}_s)^T \qquad (2\text{-}2)$$

Where, $\overline{p}_s$ and $\overline{p}_t$ represent the centroids belonging to the source point cloud part and the target point cloud part in the closest point pair, respectively. The H matrix is decomposed by SVD, from $H = U\sum V^T$, the optimal solution can be obtained as:

$$\begin{cases} R^* = VU^T \\ t^* = \overline{p}_t - R * \overline{p}_s \end{cases} \qquad (2\text{-}3)$$

We break out of the loop when the change in R and t falls below a given threshold or when we reach a set maximum number of iterations. Experimental results show that ICP algorithm can converge with the increase of the number of iterations, and the error is continuously reduced. However, beyond a certain number of iterations, the change of the error becomes stable, indicating that the algorithm has reached the convergence state.

In this study, the improved point-to-point ICP algorithm [27] was used for accurate registration. Preset feature points were used to improve the accuracy of matching before the ICP algorithm was performed. These feature points are representative points selected in the two-point clouds, such as corner points, edge points or other important feature regions. Through the mapping relationship of these feature points, an initial transformation matrix estimate is provided, which helps the ICP algorithm to carry out the iterative process better. The relationship between the ICP registration error and the number of iterations is shown in FIG. 2, where a point-to-point ICP algorithm is used for iterative optimization based on the mapping relationship of feature points. The ICP algorithm adjusts the transformation matrix by minimizing the distance error between the point clouds so that the two-point clouds are aligned as much as possible. Applying ICP algorithm to a subset of feature points can accelerate the convergence speed and improve the accuracy of registration. This method can achieve accurate matching and provide more accurate initial values when dealing with large rotation angles or long offset distances, which helps the ICP algorithm converge to accurate registration results faster.

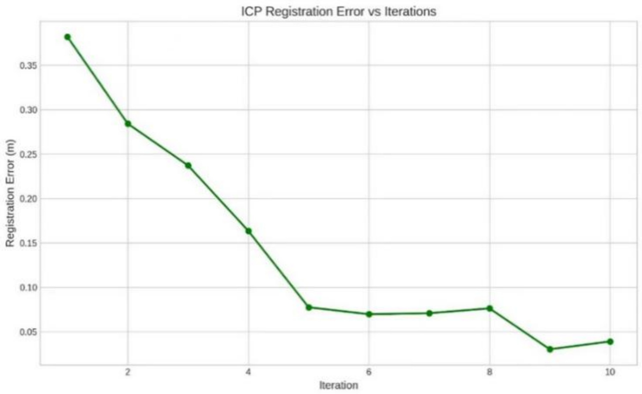

Figure 2. ICP registration error versus the number of iterations

3. System Design

3.1. System Architecture

The overall architecture of this system design aims to achieve high-precision and real-time mobile robot localization and mapping. The system is composed of hardware part and software part. The hardware part includes sensors and computing modules, and the software part covers data acquisition, sensor fusion, localization and mapping algorithms.

Based on the above requirements, the design goal of the system is to realize a multi-sensor fusion platform, combining the data of sensors such as LiDAR, camera, IMU, and using ORB-SLAM2 and Cartographer algorithms for efficient data processing and map construction. The system architecture should be modular and extensible to achieve rapid deployment and optimization in different application scenarios.

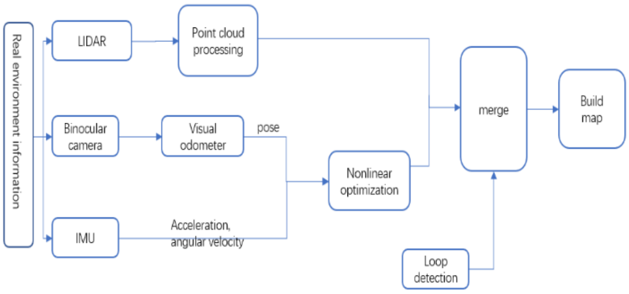

Figure 3. Overall flow chart of the system

3.2. System Hardware Design and Construction

The mobile robot used in this experiment uses a 4WD robot chassis, which is a four-wheel drive chassis with a fully enclosed structure. The sensors mounted on the 4WD chassis are mainly composed of RplidarA1M8 lidar, Inertial Measurement Unit (IMU), Mimo binocular camera MYNTEYE and wheeled odometer. The parameters of RplidarA1M8 lidar and MIMo binocular camera MYNTEYE are shown in Table 1 and Table 2. The inertial measurement unit used in this experiment is WHEELTEC N100, the specific parameters are shown in Table 3. The inertial measurement unit is small, easy to install and adjust, and has high performance and strict factory calibration. The most important feature of the measurement device is that it has a powerful Sigma-Point Kalman filter (SPKF) and a set of high-performance algorithms, which has strong anti-magnetic interference ability.

Table 1. RplidarA1M8 lidar parameters

Number	**Project**	**unit**	**Quantity value**
1	Range of distance measurement	Meter (m)	0.15-12
2	Angle of scan	Degree (Deg)	0-360
3	Angle of pitch	Degree (Deg)	-1.5~1.5
4	Ranging resolution	Millimeters (mm)	<1%
5	Angular resolution	Degree (Deg)	≤1
6	Single ranging time	Milliseconds (ms)	0.125
7	Frequency of measurement	Hertz	≥8000
8	Frequency of scanning	Hertz	5.5

Table 2. Parameters of the Mimo binocular camera MYNTEYE

Number	**Parameter names**	**Quantity value**
1	Dimensions	165×31.5×31.23mm
2	Frame rate	60FPS
3	resolution	752×480; 376×240
4	Depth resolution	752×480
5	Perspective	D: 146°H: 122°V: 76°
6	Pixel size	6.0×6.0μm
7	baseline	120.0mm
8	Focal length	2.1mm
9	Depth working distance	0.8-5m+
10	Power consumption	1w

Table 3. Inertial measurement unit WHEELTEC N100 parameters

Number	**Parameter names**	**Quantity value**		
		accelerometer	gyroscope	magnetometer
1	Range of measuring	±16 g	+2000 °/s	+4900 ut
2	Zero bias stability	<0.04 mg	<10°/hr	
3	Degree of linearity	<0.1%FS	<0.1%FS	<0.1%
4	bandwidth	260 Hz	256 Hz	200 Hz
5	Orthogonality error	±0.05°	±0.05°	±0.05°
6	resolution	<0.5 mg	<0.02 °/s	1.5Milligauss

4. Experimental Results and Analysis

4.1. Experimental Platform

In order to comprehensively evaluate the performance of the proposed multi-sensor fusion algorithm, this study conducted experiments in several test environments. The experimental platform consists of a mobile robot equipped with IMU, LiDAR, and binocular camera sensors. Cameras are used to provide real-time visual information. The hardware configuration and sensor selection of the experimental platform can ensure the robustness and accuracy of the algorithm tested in dynamic environments and complex scenes. Figure 4 shows the system hardware structure:

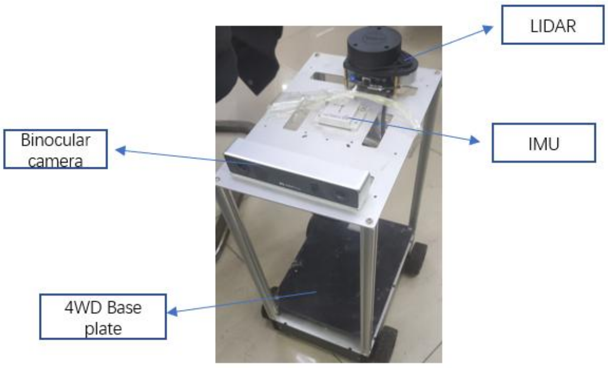

Figure 4. System hardware structure diagram

4.2. Dataset Mapping

In terms of datasets, the KITTI dataset is used, which provides rich data on indoor and outdoor environments, covering a variety of different scene types, such as dynamic obstacles, complex structures, and high-frequency changing environments. These datasets provide standardized test benchmarks for evaluating the performance of SLAM algorithms. FIG. 5 shows the results of dataset mapping.

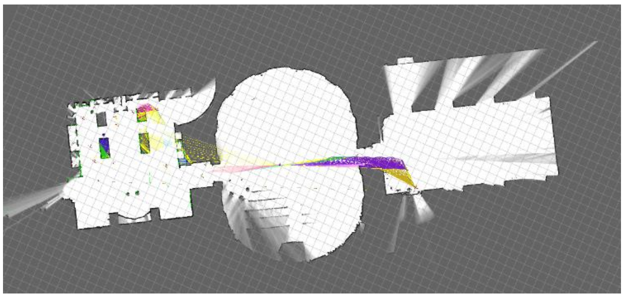

Figure 5. Builds the map based on the dataset

4.3. Realistic Environment Mapping and Obstacle Detection

In order to verify the effectiveness of the proposed multi-sensor fusion method in this study, this experiment also verifies the scene validity through experiments in the real environment (FIG. 6). By measuring the minimum distance of the reference obstacle from the sampling point in the actual map environment and the minimum distance of the obstacle model in the constructed map from the sampling point (Table 4). Compare the two to determine the accuracy of the mapping. The octree map constructed in the laboratory is shown in FIG. 7.

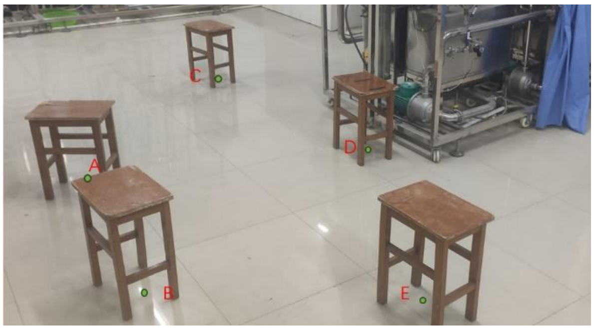

Figure 6. Laboratory obstacle detection environment

Table 4. Accuracy of obstacle recognition

Number	Actual distance /cm	measured /cm	Absolute error /cm	Relative error
AB	83	85.2	-1.8	0.021
AC	135	138	3	0.022
AE	160	157.8	-2.2	0.013
BE	90	92.9	-2.9	0.032
CD	108	110.3	2.3	0.021
CE	285	278.6	6.6	0.023
CB	230	233.4	3.4	0.014
AB	83	85.2	-1.8	0.021

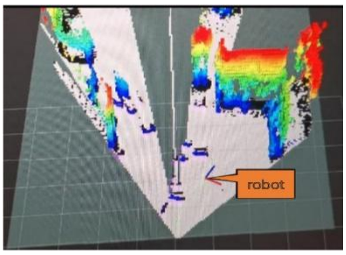

Figure 7. Building the map of the sampling points

According to the data in the table, the relative error of obstacle detection in the constructed map is about 0.02, and the mapping error when the robot rotates is larger than that when the robot moves forward. After driving a circle, the robot realized the mapping of the whole experimental environment. Figure 8:

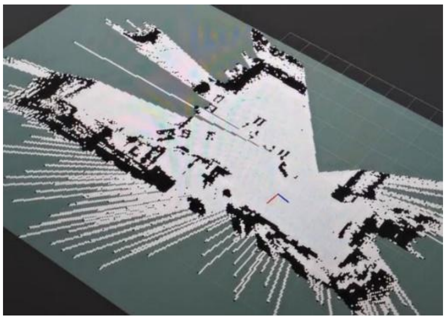

Figure 8. Mapping of the laboratory environment

4.4. Discussion of Limitations

The A1M8 lidar has a range of up to 12 meters and is limited by its low scanning frequency in highly dynamic environments. This smaller ranging range and lower scanning frequency may introduce performance bottlenecks in large-scale and highly dynamic scenarios; Binocular camera The depth estimation of the binocular camera degrades significantly in environments with low lighting or not obvious texture. Therefore, in highly dynamic and large-scale scenarios, the current hardware configuration may affect the accuracy and robustness of the experimental results. In order to improve the accuracy and robustness of the system, sensors such as solid-state lidar and event cameras with higher performance can be considered in the future. These advanced sensors can not only provide higher ranging accuracy and stronger dynamic perception ability, but also maintain high stability in complex environments, thereby improving the overall performance of SLAM systems.

5. Conclusion

Through the construction of related hardware equipment, the motion platform of this design is obtained. By optimizing multi-sensor fusion and improving ICP algorithm, the environment mapping of mobile robot in the actual environment is realized. The experimental results show that the proposed method can significantly improve the accuracy and stability of robot localization and mapping, and is suitable for outdoor and indoor environments, which is more in line with the real environment. Future work can further explore the optimization strategy of the localization algorithm to improve the localization performance of the robot in complex environments and apply the optimization method to a wider range of application fields.

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