DOI: 10.54254/2753-8818/18/20230360

Researches advanced in path planning to indoor fire escape and rescue based on SLAM

Juntao Wei[1] and Yufei Wu[2,3]

[1] Tianjin University of Technology, Tianjin, China
[2] University of Electronic Science and Technology of China, Shahe Campus, East Section of First Ring Road, Chenghua District, Chengdu, China

[3] 2018091614015@std.uestc.edu.cn

Abstract. Helping trapped people understand the external situation and provide navigation to escape the fire is the key to reducing fire casualties. Thanks to the rapid development of artificial intelligence technology, the combination of simultaneous localization and mapping (SLAM) and path planning technology has gradually become a new research hotspot, which can help provide on-site fire information, maps and navigation for trapped people and firefighters. However, improving the accuracy of SLAM techniques under harsh conditions (e.g., thick smoke, high temperature) is still an open topic. Focusing on SLAM noise reduction and path planning, in this paper, we detail the latest research progress of SLAM technology in fire escape assistance. Specifically, we first introduce the current development and application frontiers of SLAM technology, and then analyze and compare the application of SLAM technology in fire scenarios. In addition, the performance changes of the two continuous A* algorithms and the RRT algorithm during global path planning for fire scenarios are compared. Finally, we discuss the development trend of SLAM in future fire escape and rescue.

Keywords: SLAM, rescue robot, fire rescue, path planning.

1. Introduction

With the development of cities and towns, various large buildings emerge one after another, and their complex internal environment causes the potential fire hazards to appear constantly. Fires in complex public places often result in serious casualties, such as the 2001 World Trade Center in New York [1]. Fires can also occur in underground public transport systems, including the 1989 King's Cross subway station in London, which resulted in 31 deaths [2-3]. Smoke, fire sources and debris accumulated in the environment are all barriers to escape from the fire scene. To this end, how to guide the trapped people to escape early in the fire and how to assist firefighters to enter the fire scene for rescue are still the open issues.

For fire rescue, the traditional method is that firefighters enter the fire scene to rescue the trapped. However, it takes a long time from the fire to when firefighters arrive, which is the golden time to escape. Specific fire escape equipments are considered a promising supplementary solution. Depended on the developed artificial intelligence technology, fire escape based on pattern recognition, especially simultaneous localization and mapping (SLAM) technology, has gradually attracted the interest of researchers. SLAM aims to perceive the surrounding environment through sensors and help the agent to achieve localization and map construction, which can naturally be combined with fire escape tasks

DOI: 10.54254/2753-8818/18/20230360

perfectly. With this technology, trapped persons can reduce the impact of smoke, find obstacles that affect escape in advance and choose new escape routes. When firefighters enter the fire scene for rescue, this technology can guide them to quickly find trapped people and avoid dangerous situations such as fire sources and high temperatures.

However, the performance of SLAM technology are limited in real applications. the accuracy and robustness is a significant elements of a SLAM system, existing research works mainly can be divided into the following two aspects：

(1) SLAM noise reduction. Due to the influence of smoke and high temperature for sensors, the quality of data collection cannot be guaranteed. Therefore, it is necessary to select the kind of sensor used in the complex environment, which helps avoid the interference of complex environments such as smoke on map construction. In addition, it is also a feasible idea to develop more effective denoising algorithms, which aims to reduce the smoke interference.

(2) Reliable navigation. The main purpose of applying SLAM technology to fire rescue must be to reduce the casualties of trapped people and rescuers as much as possible. The necessary condition to achieve this goal is to provide a real-time and reliable navigation system. Navigation has extremely high requirements in terms of generation efficiency, route length, and collision probability. Therefore, it is extremely critical to find a global and local path planning algorithm suitable for the fire scene. The global path planning algorithm efficiently generates a fast and safe escape route based on the environment map and real-time positioning constructed by SLAM technology; For the rescue robot, the path planning algorithm strives to avoid obstacles to the greatest extent and reduce the probability of collision, while for the survivors, it is to avoid the local high temperature environment in the fire scene as much as possible.

Focusing on the above two aspects, in this paper, we survey the advanced researches and application in fire escape and rescue based on SLAM. Specifically, we study the SLAM noise reduction under harsh conditions in Section 2. The Section 3 starts with the discussion of the application scenarios of the current path planning algorithms, and then classifies the current path planning algorithms from three dimensions. The Section 4 analyzes and compares the research data about SLAM noise reduction and path planning algorithms, and Section 5 presents both disadvantages and prospects of the current SLAM noise reduction technology and path planning algorithms. Finally, we discuss the future development trend of fire escape and rescue equipment based on SLAM.

2. SLAM noise reduction

In a fire scene, smoke is the core problem that interferes with the data received by sensors. Due to the interference of smoke, some sensors cannot work properly, prolonging escape or rescue time and increasing casualties. When reducing smoke noise interference, it can be done from two aspects. First, use less affected sensors. Second, use advanced algorithms to remove noise or avoid smoke interference.

2.1. Replace the sensor

There are many types of sensors on the market, and their performance in a fire field is also different. In a fire scene, it is necessary to locate the fire source, debris and trapped persons under the condition of smoke interference. Therefore, temperature and smoke are two significant disturbance factors. In Table 1, whether some sensors will be affected and their detection distances are given. Depending on the situation, choosing the right sensor will greatly improve the success rate of escape or rescue.

Table 1. Influencing factors of different sensors.

SENSORS	**Be disturbed**			**Distance**
	Fire	Temperature	Smoke	
Radar				Medium
Lidar				Long
GPS				Long
VisCam				Close
IRCam				Medium

In fire rescue, the location of the fire source is also very important. When guiding the trapped persons to escape, it is necessary to determine the location of the fire source and guide the trapped persons away from the fire source. Common sensors used in SLAM include radar, lidar, etc. In a smoky environment, the performance of various sensors will be affected differently. For example, lidar will become useless in thick smoke, while radar is almost unaffected. However, specular reflection will cause multipath reflection and be recognized as ghost by radar, and lidar will not be greatly affected by [4]. In literature [5], the localization method of fire source based on GPS and Lidar is studied in detail. This article sets up a simulation environment and uses a telerobot equipped with LIDAR (Velodyne HDL 32), GPS (RTK-GPS), IMU and odometer sensors. The article simulates locating the fire source in the open area, but the GPS positioning in the building still has errors. Although infrared sensors can be used to quickly detect fire sources, But this article still gives ideas on how to locate obstacles other than fire sources in complex environments such as smoke.

Literature [6] experimented with the accuracy of 4 different sensors in a smoky environment and used the mean and standard deviation of δr for each localization solution to compare relative performance. First, only images from the vision camera (VisCam-Loc) are used. Second, only images from the IR camera (IRCam-Loc) are used. Third, use all available images (MMCam-Loc) from the IR and vision sensor modalities. Finally, a selected subset of images (SMMCam-Loc) found using a pre-evaluation filter. Infrared cameras are easily affected by high temperature, but there is almost no error in detection due to smoke. The visual camera is just the opposite. The combination of the two cameras can make up for each other's shortcomings. SMMCam-Loc selects the key frames of the two cameras for analysis, removes unnecessary blurred images, and further reduces errors.

2.2. *Optimized algorithm*

In practical application scenarios, there will be many problems, such as a sensor is suddenly damaged or multiple sensors cannot be used at the same time. Therefore, under the same hardware conditions, different algorithms need to be used to reduce the influence of noise such as smoke on positioning. Different algorithms have different requirements for the amount of the environment. There are some methods to perfectly avoid the influence of smoke in the fire scene, but other problems will also arise when the trapped person escapes, because the situation in the fire escape is different from the situation in daily experiments. There is a big difference. Therefore, when necessary, a variety of algorithms should be integrated to give full play to their advantages and avoid shortcomings, which can greatly increase the probability of survival of the trapped people in the fire scene, and also provide more favorable guidance for firefighters to rescue.

In literature [7], five different LIDAR-based SLAM algorithms are compared in detail, namely: HectorSLAM [8], GMapping [9], CoreSLAM [10], LagoSLAM [11] and KartoSLAM [12]. In these articles, the authors test the errors of different algorithms in a simulated environment (under ideal conditions) and in a real environment (introducing noise such as smoke). Each method has an applicable environment, and the strategy of adjusting the algorithm according to the different sensors used can obtain more accurate results.

In a smoke-filled environment, all vision-based localization methods are affected with certain errors. Pedestrian dead reckoning (PDR) is a common localization method. Because the sensor it uses will not be affected by complex conditions such as smoke and temperature, it is suitable for positioning in fire fields. The traditional PDR often loses its effect due to the accumulation of errors, so many people have done a lot of research on noise removal and error reduction in recent years. In [13], the authors combine PDR with IMU sensors and propose a more precise localization method, GPDR. The author introduced inertia into PDR control to reduce the error of each stage, thus ensuring more accurate results, and tested the performance of the system in 4 different scenarios.

In the current information age, the network has become very popular, and almost all rooms are covered by WIFI, so some people have proposed the solution of WIFI+PDR [14]. But this method also has great limitations, such as some imperceptible error values. In [15], on the basis of WIFI+PDR, the author proposes several localization methods applying different technologies, aiming to detect and eliminate these outliers, thereby improving the localization accuracy and reducing the accumulation of errors. And test the error of several methods when used alone or in combination.

(1) Outlier detection and removal strategy using machine learning (WiFi-AGNES).

(2) Based on the extracted positioning features of PDR and WiFi and the complementary features of pedestrians walking (WiFi-Chain).

(3) Hybrid scheme (Fusion) that combines WiFi+PDR with Inertial Navigation System (INS-based) Attitude and Heading Reference System (AHRS) through Extended Kalman Filter (EKF).

These several PDR-based localization methods can be completely immune to smoke and provide relatively accurate localization to the trapped person. However, there are also some problems with this method. In the above-mentioned schemes, the gait detection is usually not interrupted, that is, the subject walks the entire distance without being interrupted. However, due to the complex environment of the fire, the trapped people will fall or crouch and crawl for various reasons. PDR may not fully record data for these special cases, resulting in errors that accumulate and eventually lose their positioning. This is the problem faced by PDR applications in the field of fire.

3. Path planning algorithms

The path planning algorithm has a wide range of application scenarios in the field of robotics. It provides a solution for the field of robotics with a collision-free optimal path from the starting point to the end point. In the fire scene, a good path planning algorithm is particularly important, which will provide safe and fast navigation for the people trapped in the fire based on the environment map constructed by SLAM.

3.1. Application scenarios

The path planning algorithm is the most popular in the field of autonomous driving. The path planning algorithm will enable the autonomous car to decide the shortest and most economical route for the car's driving trajectory, and ensure that the vehicle's information is given to the system in this process: including its speed, position in the lane, and the actions of going straight, changing lanes, turning and overtaking, and traffic conditions, all of these are be used to ensure vehicle safety

At the same time, the path planning is also improving for specific models. For example in , in the off-road vehicle, the path planning algorithm will put more attention on the stability of the body, but no matter what model, safety is important. It is the most important element of path planning in autonomous driving.

At the same time, in terms of agricultural development, path planning also plays its own role. Nowadyas more and more field operations are performed by workers who do not understand the field or by autonomous vehicles. In [16], by reading the coordinates of the boundaries, the African Path planning for rectangular complex sites, ideal path planning will save a lot of professional labor and maximize profits while ensuring crop output value.

In the near future, path planning algorithms will not be limited to autonomous driving and mobile robots: for example, Elon Musk's plan to build a multi-state underground tunnel connecting major cities on the east coast; and the cutting-edge Hyper loop project, which plans to use huge Vacuum pumps and magnetic levitation technology transport people or goods at a speed of 700 miles per hour. The advantages of this project will not only be reflected in speed, but also in environmental protection. Take the transportation of people from Los Angeles to California as an example. The resource cost of using Hyperloop is only 1/20 of that of using aircraft. Such cutting-edge logistics projects as above, without the support of complex path planning algorithms, these ideas will only be limited to imagination.

3.2. Classification of Path Planning Algorithms

Path planning algorithms can be broadly divided into three categories, and each category contains corresponding strategies: (1) Reactive control (circumnavigation, motor schemas). (2) Representational world modeling (certainty grids). (3) Combinations of both.

In the current complex application scenarios, such as the above-mentioned crop scenes and other outdoor scenes, there are often unknown obstacles, however, the application of the above technologies does not ensure that we can find a perfect route to avoid obstacles. In order to avoid our robot is stuck by an obstacle. What's more, under the complex working conditions, we need advanced perception technology to obtain environmental information to ensure the safe arrival of the robot. According to the way the robot obtains the environment information, algorithm can also be further divided into the following two categories: planners based on model and planners without model.

The difference between the two categories is whether the robot has learned and acquired environmental information in advance. In the first category, the user describes the geometric model of the environment in advance, while in the second category, the robot uses various sensors for real-time acquisition of environmental information to achieve the purpose of obstacle avoidance it is obvious that the SLAM algorithm we learned in Section 2 belongs to this category.

On top of this, according to the degree of environment information obtained by the robot, we can also divide the path planning algorithm into global planning and local planning. The global planning approach assumes the availability of the map, where the surrounding environment is globally known. The local planning method is a method in which the surrounding environment is known locally, and through the reaction method using sensors like Radar and Lidar, and vision camera, the information are collected in real-time.

The global path planning algorithm can well meet our needs to find the optimal route in a static environment. However, in the real environment, the map is caused by the variability of the environment (such as the fire environment in this topic) or the error caused by the sensor. The environment is not absolutely static in most cases, so at this time we need to introduce a local environment planning algorithm, which will re-plan the local path under the changing local environment information to meet the needs of obstacle avoidance. In general, the global path The planning algorithm pays more attention to solving the needs of the shortest path, while the local path planning algorithm makes more contributions to obstacle avoidance; therefore, the combination of global and local path planning algorithms can well meet the needs of the robot to be safe and fast in fire or other scenarios. Demand for reaching the destination. The common global planning algorithm and local planning algorithm combinations are displayed as the Table 2.

Table 2. The common global planning algorithm and local planning algorithm combinations.

Method	Global path planning	Local path planning
2D Lidar-Based Robot [17]	A*	DWA
Fire Reconnaissance Robot based on SLAM [18]	A*	D*

3.3. *Global Path Planning Algorithm*

Through the above cases, it is not difficult to find that the A* algorithm is more commonly used in the field of robotics. The A* algorithm is a "search algorithm". Its idea is similar to the Dijkstra algorithm of the graph, which is essentially the optimization of the breadth-first search algorithm (BFS).

At the same time, the advantage of the A* algorithm is that the A* algorithm is a "heuristic" algorithm, which already has some prior knowledge that we tell it, such as "going towards the end is more likely to go". It not only pays attention to the paths that have been traveled, but also makes predictions about points or states that have not been traveled. Therefore, the intersection of the A* algorithm and Dijkstra adjusted the order of BFS, searched less "unlikely points", and found the shortest path to the target point faster. It allows us to weigh the speed and accuracy of the algorithm by changing the coefficients of the heuristic function. For instance, in a fire rescue we need a route as soon as possible rather than a optimal route which need a long generation time. This is also the advantage of the A* algorithm. It is very flexible, so it is very suitable for fire scenarios. The heuristic function can be formulated as equation (1).

$$f(n) = g(n) + h(n) \tag{1}$$

The heuristic function evaluates each node by calculating the comprehensive priority of each node. When the heuristic h (n) approaches 0, the priority of the node is determined by G (n). At this point, the algorithm degenerates to Dijkstra algorithm.

D* performs iterative route re-planning based on the A* algorithm. Therefore, the D* algorithm is also called the dynamic A* algorithm. When the unknown environment or dynamic obstacles appear, the A* algorithm needs to discard the initial planning. Complete the open table and close table again, and re-plan. The core idea of the D* algorithm is to use dijkstra or A* to search backward from the target point to the initial point, and then the robot moves from the starting point to the target point. When encountering dynamic obstacles, only local The change can be done, and the efficiency is significantly improved. Due to this, sometimes D* also can be regarded as the local path planning algorithms to achieve obstacle avoidance.

RRT (Fast Exploring Random Tree) is a path planning algorithm based on fast expanding random tree. By collision detection of sampling points in the state space, the modeling of the space is avoided, and the path and complex constraints in the high-dimensional space are effectively solved. Planning problems. The method can search the high-dimensional space quickly and efficiently, and using random sampling points to guide the search of the blank area in the state space, so as to find the planned path from the starting point to the end point, which is suitable for solving the complex problems of multi-degree-of-freedom robots. Static environment and dynamic environment path planning. RRT*, as its optimization algorithm, optimizes the path by recomputing existing samples; however, we find that the speed at which the sample tree expands in space depends on how dispersed it is in the sample space. Therefore, another optimization algorithm, RRT-Connect, uses two trees, which are simultaneously expanded from the first point and the target point, respectively, to optimize the generation rate.

3.4. Local path planning algorithms

The most well-known local path planning algorithms is Bug algorithm, which navigates the vehicle by local path planners using a minimal number of sensors and reduces the complexity of the online implementation.

DWA (Dynamic Window Approach), which performs optimization based on samples. It samples control actions for velocity at wide range (usually translation or angular velocity pairs) and derives trajectories for these specific sampled actions. Rollout refers to simulating the trajectory according to the robot motion model according to the specified horizontal length, and one of the important details is that the control action remains unchanged throughout the prediction range. So it cannot predict motion reversal etc. After making predictions from the samples, choose the most safe or optimal route by adjusting the coefficient of specified cost function and constraints (including distance to the global path, smoothness, obstacle clearance rate, etc.), so DWA is suitable for no inversion and does not pursue the best route Optimal but time-critical solution, ideal for differentially driven robots and supports non-smooth cost functions (consider unrolling)

4. Experiments and performance analysis

4.1. SLAM noise reduction

4.1.1. Replace the sensor. In [5], lidar and GPS are used to reduce the influence of smoke and high temperature, and the data are shown in Table 3. As can be seen from the table, the use of a single lidar will be seriously disturbed by smoke, and its error reaches 13.38m. While GPS is hardly affected by smoke, its performance inside buildings is relatively poor. After the lidar and GPS are fused, the error of the hybrid sensor can be reduced to 0.36m, which is more accurate than the 0.48m error of a single GPS.

Table 3. precision of each method of SLAM based on LIDAR and GPS.

	LIDAR+SLAM	GPS+SLAM	LIDAR+GPS+SLAM
maximum mean error	13.38m	0.48m	0.36m

For other sensors such as vision-based sensors, the effect of smoke will be greater. The data presented in Table 4 demonstrates the performance of 4 different vision sensors [6] in smoky environments, which are pure vision cameras, infrared cameras, hybrid cameras, and a selected subset of images found using pre-evaluation filters. The authors experiment with four sensors in different scenarios. It can be seen from the table that the deviation difference between the infrared camera in the normal environment and the smoke environment is small, which proves that the smoke has little effect on the infrared camera.

But the performance of the vision camera in the two environments is very different, and the deviation value of the error increases by about 40mm. The hybrid camera also performed poorly in smoky environments, increasing its error by about 60%. Finally, the method of intercepting key frames can effectively reduce the influence of smoke, and its performance is better than using a single infrared sensor.

Table 4. local differences in position (δr) between estimated trajectories and the reference.

Localisation Solution	Period	Mean Local Evaluation
		δr (mm)
IRCam-Loc	Clear	22.90
	Smoke	21.55
VISCam-Loc	Clear	18.65
	Smoke	62.05
MMCam-Loc	Clear	16.50
	Smoke	26.15
SMMCam-Loc	Clear	15.70
	Smoke	19.75

4.1.2. Optimized algorithm. After the analysis of [7], five common SLAM algorithms are given, and the authors also test their performance in the simulated environment and the real environment respectively. The data are shown in Table 5. Except for CoreSLAM, the other four algorithms are affected by the smoke. Although CoreSLAM is not affected by smoke, its error is larger than other algorithms, up to 30 times the error. Therefore, it is necessary to use the most suitable algorithm to optimize the results in different environments.

Table 5. Errors of five different algorithms.

Experiments	HectorSLAM	Gmapping	KastoSLAM	CoreSLAM	LagoSLAM
Simulation	0.4563	0.4200	0.5509	11.8393	1.4646
Real world MEAN	0.9241	1.5005	0.7713	10.0940	2.0327

There are some localization methods that can avoid the effect of smoke well, such as PDR. However, the traditional PDR error is very large. In Table 6, it can be seen that the error reaches 16.87m. This error is very fatal indoors. Such a large error makes the trapped person locate. On the basis of PDR, introducing other conditions to constrain the positioning will minimize the error. The GPDR in [13] is the result of adding inertial constraints, and its error is reduced to 1.73m, which is an acceptable data indoors. Different solutions are also given in [15]. Fusion can reduce the error to 1.67m. On this basis, adding WIFI positioning and complementing it can further reduce the error by 0.25m. The accuracy of using WIFI positioning alone is not as good as the hybrid algorithm, but it can also be used in emergency situations. Selecting appropriate algorithms and using them at the same time can further increase the positioning accuracy.

Table 6. Errors of PDR and its Derived Algorithms.

Methods	Mean Error(m)
GPDR	1.73
Fusion +WiFi-AGNES +WiFi-Chain	1.19
Fusion +WiFi-AGNES	1.44
Fusion +WiFi-Chain	1.42
Fusion	1.67
PDR	16.87
All-WIFI	2.10
WiFi-Chain WiFi	1.23
No-WiFi-Chain WiFi	4.39

4.2. path planning comparison

4.2.1. Performance metrics in path planning algorithms. As mentioned in 3.1, the ultimate goal of path planning is to find the optimal path while avoiding obstacles safely, and the optimal path can be either the smoothest path, the shortest path, or the vehicle that can travel at the highest speed The moving path can be called the best path, so the route length of the path, the speed of passing the path, the safety of the path, and the collision probability can all be used as performance indicators of the path planning algorithm. In addition, the resources occupied by the path planning algorithm, such as memory and the number of processes, can also be used as its performance indicators.

Since the rescue rate is the main purpose in the fire scene, we are most concerned about the generation rate of the path at that time, which is undoubtedly the key factor in reducing the mortality rate. An excellent global planning algorithm will quickly indicate a safe escape route for survivors. According to the description in Section 3.3, the global path planning algorithm is the key to generating the optimal route, so we first compare the main algorithms in the global path planning algorithm.

4.2.2. Comparison of global path planning algorithms. From 3.2, we learned that the A* and RRT algorithms and their optimization algorithms are the common global path planning algorithms. Therefore, we will compare the A* algorithms with different consistency and the RRT algorithm optimization algorithms in different scenarios. A* searches the space discretized with dispersion degree of 0.5 and RRT series algorithms search in the continuous space. The max steer distance is 0.5 and the probability of using the goal as the sample point is 0.1.

Table 7. Path Length of Different Test Cases and Planners.

Algorithms	Single cube	maze	window	tower	Flappy bird	room	monza
A*-1	8.32	79.29	27.06	32.80	25.30	12.07	78.03
A*-5	8.32	81.46	27.78	39.36	29.76	12.66	78.41
RRT	10.16	120.76	31.12	43.87	39.15	19.52	107.38
RRT*	8.56	79.78	24.86	31.29	28.70	14.84	76.78
RRT-Connect	8.29	121.61	30.99	45.46	42.04	13.86	105.90
RRT*-Connect	8.17	88.52	26.46	33.49	29.22	14.81	77.59

The performance of the six path planning algorithms in terms of the length of the generated path is shown in Table 7. Because the A* algorithm uses a discrete space of 0.5 dispersion, the data shown in the table is sub-optimal, but we found that A* in various scenarios is almost the best, and the path length of the A* algorithm under the two consistency is almost the same; While in the RRT algorithm, because RRT* is an optimization algorithm which recalculation the existed sample points to optimizes the path, so its performance on the route length is the best, but at the same time it will sacrifice a part of the genneration time, which we can find in Table 8.

Table 8. Used Time of Different Path Planning Algorithms.

Algorithms	Single cube	maze	window	tower	Flappy bird	room	monza
A*-1	0.24	102.07	30.37	27.07	19.93	3.85	11.13
A*-5	0.02	74.00	0.38	3.18	3.26	1.05	8.09
RRT	0.0403	40.07	0.25	2.22	0.48	0.46	34.05
RRT*	0.17	170.05	0.86	10.83	2.40	2.19	243.91
RRT-Connect	0.003	36.91	0.10	1.91	0.39	0.08	15.22
RRT*-Connect	0.004	238.97	0.40	7.10	1.12	1.21	57.41

Table 8 shows the comparison of the path generation time of the six path planning algorithms. It can be seen that although the A* algorithm achieves the best path length, it requires a long computing time in a complex environment. In a complex environment such as a maze, the A* algorithm will rewrite a large number of open and close tables when encountering obstacles, which greatly prolongs the operation time. The RRT series is much faster than the A* algorithm in most cases because its algorithm does not need to model the space, while the RRT-Connect uses both the endpoint and the starting point as the sample tree to calculate the feature in the path. The best in terms of generation rate.

Comprehensively comparing the two indicators of the six planners in different cases, the 5-consistent A* will be a good method for us to apply in practice, although in complex environments, it will use long time to generate route due to rewriting tables., but considering that the indoor characteristics of most fire buildings will not be too complicated, compared with the RRT algorithm, A* with 5 consistency will be the best algorithm we apply to fire rescue. When applied to the rescue of complex environments, we can consider replacing the A* algorithm with the D* algorithm as an optimization. Although D* will sacrifice certain computing resources, it will greatly reduce the computing time due to the dynamic optimization of the D* algorithm.

4.2.3. Comparison of local path planning algorithms. There are many common algorithms in local path planning. Considering the portability of fire scenarios, the local path planning algorithm should be optimized as far as possible in terms of operation cost and sacrifice more computing resources to global path planning algorithms. Common local path planning algorithms are qualitatively compared in Table 9.

DOI: 10.54254/2753-8818/18/20230360

Table 9. Characteristics of various path planning algorithms.

Path planning	Required memory	Required processin g	Features
Uniform discretization	8	5	Simple implementation
Quadtree discretization	5	8	Large computations and uniform path
Triangular discretization	2	5	Keep away from obstacles
Trapezoidal discretization	2	5	Keep away from obstacles
Voronoi algorithm	5	8	Maximum distance from obstacles
Visibility graph	5	5	Shortest path
Bug1	1	2	Simple implementation and great obstacles avoidance
Bug2	1	2	Simple implementation and great to obstacles avoidance
Gradient field	7	8	Sticking to local points
Vector field histogram	5	8	Especially for path planning based on sonar sensor

For the local path planning algorithm that prioritizes obstacle avoidance, the efficiency of obstacle avoidance and the route change made for sudden changes in the environment will be the most important comparison factors, because the biggest obstacle in the fire scene is the local high temperature environment. Therefore, it is particularly important to survey the high temperature environment in real time and consider it as an obstacle factor in the update of the route in the process of generating the route. Among the above algorithms, the occupancy of computing resources and the characteristics of the algorithm are weighed, we think the Triangular discretization and Trapezoidal discretization are good choice as a local path planning in fire condition, they have a smaller resource occupancy and both of the keep a good distance from the obstacles which means that in a fire, they can well guarantee users away from high temperature areas and ensure the safety of them.

5. Current problems and future prospects

5.1. Difficulties of noise removal

Almost all the current mainstream sensors have a good guarantee of their accuracy, but their performance in extreme environments (such as high temperature, thick smoke, etc.) is not satisfactory. Some sensors are not designed and intended to be used in extreme environments such as fire fields. Different sensors are affected by different factors. For example, visual cameras are almost paralyzed in a thick smoke environment, while inertial sensors are completely unaffected by smoke. How to choose the appropriate sensor to apply to SLAM and provide help to the trapped person based on this is a hot topic at present. In addition to this, different algorithms can have different effects on the results when using the same sensor. Although the accuracy of various algorithms and sensors varies in experiments, it is difficult to prove that one method is always better than the other in practical applications. Choosing the right method under different circumstances is the key to solving the problem. But the biggest problem currently facing is that the results are not accurate enough. In the case of indoor positioning, an error of several meters may cause rescuers to be unable to determine the location of the trapped person, which is a fatal flaw.

In the future, a single sensor is no longer applicable, and fusion sensors and fusion algorithms can better improve accuracy. At the moment it appears that in either case, using a single sensor for positioning will greatly increase the error. Therefore, after summarizing a lot of data, this paper found that the use of fusion sensors and fusion algorithms can greatly improve the accuracy. The reason is that each sensor has a physical quantity that it is good at detecting, and when several sensors are used at the same time, errors that may occur are filtered out. This ensures the accuracy of the results. However, in some special cases, such as when there is not enough space to install multiple sensors, it is necessary to

DOI: 10.54254/2753-8818/18/20230360

use fusion algorithms to calculate and analyze the measured data to ensure its accuracy.

5.2. Difficulties of path planning

We introduced the current and future application frontiers of path planning in chapter 3.1.2, mostly high-speed and low-cost transportation scenarios, and in terms of algorithms, the main problems of the current path planning algorithm can be solved by the path planning in chapter 3.4. The comparison of the algorithms shows that it is not difficult to find that the current path planning algorithm faces a trade-off between the running speed, the running cost (memory, process occupancy), and the degree of route optimization in a complex environment, that is to say, in the current path The main direction of the planning algorithm is to simultaneously improve the traditional algorithm among the three final path planning algorithm indicators.

With the continuous improvement of robot autonomy, it has the ability of environmental perception and environmental learning. Many scholars have proposed deep reinforcement learning algorithms to solve the problem applying path planners for robots in dynamic and complex environments. The deep reinforcement learning algorithm makes full use of the advantage of deep learning and reinforcement learning: advantage: great perception and decision-making. Through the continuous trial and error of the interaction process between the robot and the environment, and through the feedback of environmental evaluation, the system realizes more intelligent decision-making control, and helps the mobile robot in a certain environment. In some complex and unknown environments, a certain degree of autonomy and intelligence can be achieved, but at present, the neural network algorithm through intelligent bionics is faced with the problems of high hardware requirements and difficult parameter adjustment.

5.3. Combination of SLAM and AR technology in fire rescue

After we have comprehensively studied the application of SLAM technology in fire rescue at this stage, we found that the current application of SLAM technology in current rescue scenarios is mostly applied in the form of rescue robots. The best escape time is often in the early stage of the fire. Considering the travel time of the firefighters after receiving the alarm call, the trapped people often hide in closed indoor spaces, such as bedrooms and bathrooms, because they cannot respond to external conditions. Accurate judgment or being in a passive situation due to being blocked by thick smoke, so helping the trapped person to understand the external situation and provide navigation will provide more powerful help in reducing the death rate of fire, we consider the application of SLAM in future fire rescue The development trend will be towards AR (augmented reality) head-mounted devices designed for trapped people, which will be well integrated into existing gas masks, measure the external environment through sensors, and use SLAM technology Help the trapped to provide navigation in thick smoke conditions, so that the survivors are more active in fire self-rescue, and greatly reduce the casualties caused by the fire.

6. Conclusion

This paper expounds two feasible methods of SLAM noise reduction, including replacing the sensor and updating the algorithm. Below this, different methods are introduced and their results analyzed. Several different ideas for avoiding the effects of smoke and fire sources are listed. It is found that the use of fusion sensors and fusion algorithms is an effective means to improve localization accuracy.

Then, on the basis of completing the mapping and positioning, the application of the path planning algorithm is further elaborated. First, the application scenarios of the path planning algorithm in various fields and the current development frontier in the direction of transportation are introduced, and then the path planning algorithm is analyzed from three dimensions. The planning algorithms are classified, and the main path planning algorithms under the classification of global planning and local planning are introduced. Finally, the path planning algorithms in the same category are compared through quantitative analysis, and the path planning algorithms in the fire scene are selected. More applicable path planning algorithm.

References

[1] Torero J L. Fire-induced structural failure: the world trade center, New York[J]. Proceedings of the Institution of Civil Engineers-Forensic Engineering, 2011, 164(2): 69-77.

[2] Fridolf K, Nilsson D, Frantzich H. Fire evacuation in underground transportation systems: a review of accidents and empirical research[J]. Fire technology, 2013, 49(2): 451-475.

[3] Njå O, Svela M. A review of competencies in tunnel fire response seen from the first responders' perspectives[J]. Fire safety journal, 2018, 97: 137-145.

[4] Dogru S, Marques L. Using radar for grid based indoor mapping[C]//2019 IEEE International Conference on Autonomous Robot Systems and Competitions (ICARSC). IEEE, 2019: 1-6.

[5] bin Shamsudin A U, Mizuno N, Fujita J, et al. Evaluation of LIDAR and GPS based SLAM on fire disaster in petrochemical complexes[C]//2017 IEEE International Symposium on Safety, Security and Rescue Robotics (SSRR). IEEE, 2017: 48-54.

[6] Brunner C, Peynot T, Vidal-Calleja T. Combining multiple sensor modalities for a localisation robust to smoke[C]//2011 IEEE/RSJ International Conference on Intelligent Robots and Systems. IEEE, 2011: 2489-2496.

[7] Grisetti G, Stachniss C, Burgard W. Improved techniques for grid mapping with rao-blackwellized particle filters[J]. IEEE transactions on Robotics, 2007, 23(1): 34-46.

[8] Santos J M, Couceiro M S, Portugal D, et al. A sensor fusion layer to cope with reduced visibility in SLAM[J]. Journal of Intelligent & Robotic Systems, 2015, 80(3): 401-422.

[9] Kohlbrecher S, Von Stryk O, Meyer J, et al. A flexible and scalable SLAM system with full 3D motion estimation[C]//2011 IEEE international symposium on safety, security, and rescue robotics. IEEE, 2011: 155-160.

[10] Steux B, El Hamzaoui O. tinySLAM: A SLAM algorithm in less than 200 lines C-language program[C]//2010 11th International Conference on Control Automation Robotics & Vision. IEEE, 2010: 1975-1979.

[11] Carlone L, Aragues R, Castellanos J A, et al. A linear approximation for graph-based simultaneous localization and mapping[C]//Robotics: Science and Systems. 2012, 7: 41-48.

[12] Vincent R, Limketkai B, Eriksen M. Comparison of indoor robot localization techniques in the absence of GPS[C]//Detection and sensing of mines, explosive objects, and obscured targets XV. SPIE, 2010, 7664: 606-610.

[13] Wu R, Pike M, Chai X, et al. Gaitpdr: Using Gait Analysis for Heading Estimation in Pdr Based Indoor Localization Systems[J]. Available at SSRN 4045876.

[14] Yu J, Na Z, Liu X, et al. WiFi/PDR-integrated indoor localization using unconstrained smartphones[J]. EURASIP Journal on Wireless Communications and Networking, 2019, 2019(1): 1-13.

[15] Zhang Z, Liu J, Wang L, et al. An enhanced smartphone indoor positioning scheme with outlier removal using machine learning[J]. Remote Sensing, 2021, 13(6): 1106.

[16] Jin J, Tang L. Optimal path planning for arable farming, 2006 Portland, Oregon, July 9-12,2006.

[17] Xuexi Zhang, Jiajun Lai, Dongliang Xu, Huaijun Li, Minyue Fu, "2D Lidar-Based SLAM and Path Planning for Indoor Rescue Using Mobile Robots", Journal of Advanced Transportation, vol. 2020, Article ID 8867937, 14 pages, 2020.

[18] Li S, Feng C, Niu Y, Shi L, Wu Z, Song H. A Fire Reconnaissance Robot Based on SLAM Position, Thermal Imaging Technologies, and AR Display. Sensors (Basel). 2019 Nov 18;19(22):5036. doi: 10.3390/s19225036. PMID: 31752251; PMCID: PMC6891496.