Research on ROS-based AGV Navigation System

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Abstract

Navigation is a core issue in mobile robot research. This paper analyzes the current main methods of localization and navigation of mobile robots including AGV, introduces the research status of mobile robot localization and navigation system, and discusses the navigation technology, localization method and path planning technology of indoor mobile robot for AGV. Mainly introduces the Monte Carlo localization algorithm and artificial intelligence path planning technology. In the existing research of localization and navigation, AGV autonomous navigation system based on ROS platform is built.

Keywords

Navigation; AGV; SLAM; Localization .

1. Introduction

Automated guided vehicle (AGV) as an automated logistics equipment, more and more used in material handling and assembly. Navigation technology is one of AGV's core technologies. Compared with the traditional AGV, today AGV integrates more advanced technologies and is gradually becoming a comprehensive set of functions such as task planning, environment creation and autonomous localization, path planning, real-time navigation and target recognition System [1].

Autonomous localization and navigation means that mobile robots perceive external environment information through their own sensors in an unstructured environment and process the environmental information to estimate the current three-dimensional coordinates and moving directions of the robot and determine the target to be reached by the robot Point information, control instructions obtained by the control system to avoid the obstacles in the process of moving safely and quickly reach the designated destination [2]. Localization and navigation technology is the core and foundation of real autonomous control and true intelligence of mobile robots. It has always been a hot issue in the research field of mobile robots.

2. Research Status of AGV Navigation System

The first prototype of AGV was introduced in 1913. Ford first used rail guided AGV instead of conveyor in the production of the assembly chassis, which shortened the assembly time by 1 hour and 33 minutes, fully embodying the AGV's Efficient. From then on, AGV officially entered the production practice. In 1953, the United States Barrett Electric company developed the world's first use of electromagnetic induction navigation AGV. Due to the high efficiency of AGV trolleys in production, it has developed extremely rapidly. In the late 1950s, AGV was widely used in European countries. In the 1960s, computer technology was applied to the AGV system, and the application of AGVS was extended from automated warehouses to flexible processing systems. In the 1970s, AGV was expanded to the production system of the company, and AGVS developed rapidly. It is due to its high efficiency; in the 1980s, with the advancement of computer technology, the performance of AGVS has been greatly improved, and the production cost has been greatly reduced, making AGV

develop rapidly and develop independently into an industry; in the 90's, AGVS With the development of networking, digital information, and intelligent development, and the first international conference on unmanned trucks held in London in June 1981, this landmark conference enabled the AGV technology to be greatly exchanged and developed.

The application scope of AGVS in industrial developed countries such as Europe, the United States, Japan, etc. has been very extensive, and it is moving toward a specific direction. Many factories have adopted AGVS as a flexible manufacturing assembly system for vehicles. At present, the advanced development direction of AGV is that it can work under the needs of specific work environment without fixed lines, full operational capability, and overload and high-precision localization.

3. AGV navigation technology

3.1 AGV Navigation Technology Classification

There are many ways to classify AGVs, and different focuses have different classification methods. AGVS is a complex system. The navigation method is the core technology of AGV navigation technology. According to the classification of navigation methods, there are the following common types, following a brief introduction.

In accordance with the navigation, the common way can be divided into the following categories:

(1) Electromagnetic navigation

This type of navigation is one of the earliest and is still one of the navigation methods currently in use. This navigation method is to lay the wires under the ground in accordance with a predetermined planning path. The wires are fed with alternating current. The alternating current is generated by the AC frequency generator, which is low voltage and low frequency. After the line is powered on, a magnetic field is generated with the line as the center axis. Two magnetic induction coils are provided on the AGV, and the voltage value corresponding to the magnitude is generated by the strength of the detected magnetic field. If the trolley deviates to the left of the preset wire when driving, the voltage value sensed on the right side of the magnetic induction coil is higher; otherwise, the voltage value on the left side of the magnetic induction coil is higher. This voltage value is the input signal that controls the drive motor. Drive the motor to control the body to travel along a preset wire, which is the default path. The advantage of this navigation method is strong anti-pollution ability, the ground line line is not easy to damage, easy communication control, navigation principle is simple, stable and reliable. The disadvantage is that the flexibility of the path change is poor, and changing the path is inconvenient.

(2) Tape navigation method

This navigation is the tape instead of electromagnetic navigation buried in the ground under the wire. Compared with the first way, this method has better flexibility, easier path changing and easier laying. However, since the path tape is laid on the surface, the path is easily contaminated and is also susceptible to interference from the surrounding metal to the magnetic field of the tape. Therefore, this navigation requires a higher working environment.

(3) Laser navigation

This navigation method is pre-installed with location-accurate laser reflectors at certain positions around the intended travel path of the AGV trolley. By receiving the reflected laser beam, the AGV can locate its current position and direction of travel through continuous triangulation. The advantages of this navigation method are the simple design of the laser reflector and the good flexibility of changing the route. The disadvantage is that this navigation method requires a higher accessibility to the environment.

(4) Photoelectric navigation

The principle of this navigation method is to set a path of a specific color and shape on a preset path in a working environment and detect a path marking by using an infrared or a photoelectric probe to

determine a relative offset between the body and a path so as to control a car The operation of the body. The biggest advantage of this navigation is the low cost; the disadvantage is that the operating environment, especially the cleanliness of the surface of the route requirements are high, once the path is contaminated, will greatly affect the body's navigation.

(5) Inertial navigation

The principle of this navigation method is to use the gyroscope to detect the azimuth of the AGV body during operation and to determine the current position by the travel distance determined by a reference reference point and to control it by comparing it with the known route map data Car body operation. The advantage of this navigation method is flexible and good compatibility, especially for the dorsal models; the disadvantage is the need for map information, more resource-intensive, large amount of computation.

(6) Visual navigation

The navigation method is to obtain the path information around the working environment or the ground via the optical camera and then determine the deviation of the vehicle body from the predetermined route or path by image matching or image processing to extract the characteristic value and then control the operation of the vehicle body . Specifically speaking, it is divided into two kinds. The first method is based on the visual navigation mode of the scenery understanding. It needs to pre-establish the environment image database around the preset route, and then the AGV uses the camera to capture the surroundings of the driving route in real time The image information is then matched with the image stored in the aforementioned database for image feature matching to control the vehicle body operation. The advantage of this navigation method is that it does not need other auxiliary equipment and does not need to lay out the preset route, and the cost is relatively low. However, its shortcoming is very obvious. First, it is very difficult to traverse the environment database around the path; secondly, High real-time requirements. The second method is based on the image recognition of the navigation route. A navigation line of a certain color and size is set on the required route. The camera preloaded on the vehicle body acquires the planned navigation route image in real time. After the correction The offset between the navigation line and the car body can be calculated so that the car body can be controlled to run along the guide line.

(7) Multi-sensor information fusion navigation

The navigation based on multi-sensor information fusion uses various sensors installed on the AGV to obtain environmental information and then complete navigation. Common sensors include LIDAR, sonar, infrared and ultrasonic. This navigation method uses sensors to detect obstacles in the surrounding environment, and then performs localization, map construction, and path planning. Since the distance to the obstacle is measured using the transmitted signal and the received signal, its accuracy is easily affected by the environmental conditions. However, this navigation method has the characteristics of non-contact and fast response, so it is commonly used in the recent popular multi-sensor information fusion technology [9].

In addition, by judging whether the environmental information is complete and the types of indication information used for navigation are the same, the categories of navigation can be classified into the following categories:

Use map navigation [10]. The navigation of the map needs to provide the already created map to the AGV in advance. The map may be in the form of an environment-based geometric model or a topological map, but must contain sufficient environmental information. The AGV relies entirely on the map, using path-tracking and obstacle avoidance, to enable navigation.

Navigation using maps created in real time [11]. Navigation with map created in real time Perceptual environment with various sensors of the AGV and thus a map describing the environment is constructed in real time and then navigated. The sensor can be an AGV's own odometer, or it can be installed sonar, lidar, camera, etc.

Do not use map navigation [12]. Without using the navigation of the map to perceive the surrounding environment information through the sensors of AGV, AGV had no knowledge of the environmental information before, and then the navigation is completed through the identification or tracking technology.

The above navigation methods have their own advantages and disadvantages. However, due to the AGV in the work environment, there are often many unknown moving obstacles, including the raw materials temporarily stacked in the workshop, the walking staff or other robots, and the unstructured environment. Which will increase the difficulty of navigation. Therefore, there is still tremendous potential for development and broad prospects for AGVs to be capable of navigating obstacle avoidance in dynamic, unknown, structural or unstructured environments.

3.2 Environmental map construction

The construction methods of the environmental map mainly include a grid map method, a geometric map method, a topological map method and a Simultaneous Localization and Mapping (SLAM).

The raster map representation [13] was first proposed by Moravec and Elfes. This method divides the working environment of the robot into a series of grids with probability values, and the probability value indicates the probability that the grid is occupied by obstacles. size. The creation of a grid map depends on the robot pose of the perception point. Once the pose of the robot is determined, the newly perceived local grid map is fused into the global grid map to obtain a more definite grid map. It is relatively easy to create and maintain a grid map. The perceptual information of each grid in a raster map can directly correspond to a certain area in the environment, and various information in the entire environment can be retained as much as possible. The grid map is very suitable for the processing of sonar ranging or laser ranging data, and it can easily perform robot localization and path planning. However, the higher the spatial resolution of the environment, the smaller the grid, which will increase the computational time and space complexity.

Topological maps use nodes and the connection relationships between nodes to describe the environment and do not require explicit geometric information. The topological map is particularly suitable for describing a structured environment. Its advantages are that it is easy to manage, has a high degree of abstraction, and does not require precise description of geometric parameters. The definition and identification of topology map nodes are difficult. The first way to define a node is to select corridors, doors, walls, corners, etc., as the given node. The second definition method is a location-specific method that extracts a specific location from the sensor information as a node. Classically, the sonar information and magnetic compass information are identified and nodes are identified. In addition, the third method is to extract features from the measured values of the sensors and compare similarities of the extracted features. Similarity is defined as nodes [14]. Topological maps can be created either by extracting nodes and their associations from a raster map, or by using sensor initial information, such as the generalized Voronoi map creation method.

The feature map describes the environment in terms of location parameters of the environment landmark features in the global coordinate system. Geometry maps represent the environment as many sets of parameterized feature values such as points, lines, areas, and so on. Most of the feature maps are created based on the external sensor's detection data of the environment. In a structured indoor environment, the environment space can be represented by some simple collection model; for the outdoor environment, the environment space can be represented by a curved surface. Chatila [15] first used a polygonal map to describe the structure of the environment and used laser ranging data to predict the position of the robot.

The simultaneous localization and map creation (SLAM) problem of mobile robots can be described as follows: In an unknown environment, a robot starts from an unknown location, self-locates according to position prediction and sensor perception, and simultaneously creates an environmental map during

the movement. The common simultaneous localization and map creation SLAM can be divided into the following categories:

(1) SLAM based on Extended Kalman Filter (EKF)

The extended Kalman filter method is based on the linear system and proposes one of the most common SLAM methods to solve the estimation problem of the nonlinear system. The method uses planar coordinates to represent the location of the robot and the environment features, and describes the relationship between the robot movement and the environment features as two nonlinear models: a robot movement model and an observation model. Through these two models, the use of extended Kalman theory to achieve, including the two stages of prediction and update [16].

(2) SLAM based on Unscented Kalman Filter (UKF)

The Unscented Kalman Filter (UKF) is an algorithm framework based on the untracked transform and EKF [17]. The basic idea is to approximate a Gaussian distribution, which is much easier than approximating any kind of non-approximation equation. The model is linearized to reflect the characteristics of the entire system more realistically. For any non-linear system, using UKF can obtain system posterior mean and covariance estimation accurate to the third moment. Like the EKF, the UKF makes Gaussian assumptions about the posterior density of the nonlinear system. It is still not suitable for the general non-Gaussian distribution model. Therefore, the use of UKF has certain limitations.

(3) SLAM based on particle filter (PF)

Particle filter localization methods are also referred to as Sequential Monte Carlo methods (SMC). In sequential Monte Carlo localization, a large number of particles are used to represent the robot's position. The probability density function is approximated by finding a set of random samples propagating in the state space, and the mean value is replaced by the sample mean to obtain the minimum variance of the state. The estimated process, these samples are called "particles." The mathematical language is described as follows: For a stationary random process, assuming that the posterior probability density of the system at time k-1 is p, n random sample points are selected according to a certain principle, and after the measurement information is obtained at time k, the state and time update process is performed. The posterior probability density of n particles can be approximated as p. As the number of particles increases, the probability density function of the particle gradually approaches the probability density function of the state, and the particle filter estimate achieves the effect of the optimal Bayesian estimation.

The particle filter algorithm gets rid of the constraint that the random variables must satisfy the Gaussian distribution when solving the non-linear filtering problem, and solves the problem of lack of population samples to a certain extent. Therefore, the algorithm has been successfully applied in many fields in recent years. Both the conference and discussion groups used particle filtering as a topic for in-depth discussions and academic exchanges.

(4) SLAM based on thin node point tree filter

Based on the SLAM method of the thin node point tree filter, the Bayesian network approximate reasoning method is used to solve the SLAM problem. The basic idea is to treat the state in the Kalman filter as a time-varying Gaussian graph model, using direct or indirect node dependencies to express the correlation.

(5) SLAM based on collective estimation theory

The basic rationale for estimating the SLAM problem based on the set of staff is that all errors are indeterminate, but they can all be assumed to be within a certain range. The set-members estimation method uses an achievable set to estimate the positions of the robot's poses and landmarks, and a combination of two sets of realizable sets can be obtained by solving the intersection of these two achievable sets. In the SLAM problem, since the observation model is generally a complex nonlinear

equation of robot poses and landmarks, the resulting achievable set is generally a non-convex set surrounded by nonlinear curves, and it is very difficult to accurately calculate the achievable set. Some approximation sets of techniques must be used to satisfy the requirements for recursive updating and real-time performance of an implementable set with efficient algorithms.

(6) SLAM based on spatially extended information filter

This method was proposed by Sebastian Thrun et al. and is an improvement over the EKF algorithm. It no longer uses the covariance matrix to represent the spatial information correlation. Instead, it uses the spatial information matrix to represent the intrinsic intrinsic relationship among the spatial information, and uses the meshed data structure to maintain only the neighboring environmental features (maps).

3.3 Localization

3.3.1 Robot localization method

According to the different sensors used by the robot, the robot localization method can be divided into two kinds of relative localization and absolute localization.

Relative localization refers to calculating the pose of the robot at the current moment through the pose of the robot at a time and the relative displacement and orientation change in the current time period. This method is also called the dead reckoning algorithm. The direct movement measurement sensors mainly include displacement measurement sensors such as an odometer and an accelerometer, and gyro, differential odometers, inertial measurement units (IMU), and other heading sensors. In addition, in the field of computer vision, it is also possible to estimate the relative pose transformation quantity by using an environment-sensing sensor such as a camera and matching two adjacent frames of environmental observations, which is also called a visual odometer [18]. By directly measuring the sensor to achieve low relative localization cost, the algorithm is simple and fast, but the accuracy is not high, the error is relatively large, vulnerable to environmental impact, such as wheel slippage will produce a large random error. The visual mileage accuracy can be very high, but the calculation is relatively large, the implementation is more complex and the processing speed is slower. Researchers have been able to achieve relatively accurate relative motion estimation through multi-sensor information fusion. The most common fusion methods are extended Kalman filter [19] and unscented Kalman filter [20]. However, theoretically, even if the relative localization error is small, it will accumulate over time, and the cumulative error still exists. Therefore, in actual situations, relative localization is usually only applicable to short-term, short-distance travel situations.

Absolute localization mainly uses navigation signs, map matching, GPS and other methods to locate the robot's absolute position in the world coordinate system. The cost of the construction and maintenance of navigation signs is relatively high, and the environment needs to be modified. GPS is generally only suitable for outdoor use. The error is relatively large and accurate localization cannot be achieved. The map matching technology uses sensors such as sonar, camera and laser to sense the information of the environment, and compares the observed information with the previously constructed map to determine the position of the robot in the map. Among them, two key issues are the construction of map models and the choice of matching algorithms. Absolute localization based on map matching can achieve high-precision localization and is therefore the mainstream method of robot localization, especially in the indoor environment. However, searching the entire map for current observations is time-consuming, and its time increases exponentially as the map increases. Therefore, it is impossible to achieve real-time localization by performing observation matching on the entire map every time.

In general, relative localization processing speed is fast, but the error will continue to accumulate; absolute localization does not exist cumulative error, but the processing speed is slow. The two together, can form a complementary, to achieve better localization effect. Any single sensor and localization method has its own limitations and cannot ensure accurate localization at any time. Therefore, through the multi-sensor information fusion method, a variety of localization technologies

can be combined to overcome the incompleteness of a single sensor, thereby achieving accurate and stable localization. Most mature and stable robot localization methods combine relative localization and absolute localization to perform combined localization.

3.3.2 Two-dimensional map localization method

In robot localization, there are two main types of information to be obtained, one is the movement information of the robot, that is, the relative movement of the robot at any two moments, and the other is the observation information, that is, the robot senses the information in the environment through the sensor, Sensors such as laser, camera, RGB camera, etc. The entire robot's localization process can be described as "taking one step at a time". Each step of the robot first estimates the current pose by relative motion and then matches the current observation with the map to correct the estimation of the pose Repeat this process to achieve pose estimation at any time.

Since the 90s of last century, the method of probabilistic locating plays a dominant role in robot localization. It mainly uses the Bayesian theory to combine the motion information of the robot with the observational information, and estimates the pose of the robot through probability derivation The probability distribution. The advantage of probabilistic methods is that robots present noise and uncertainty when measuring information and probabilistic methods establish accurate probabilistic models for different noise sources and their effect on the measured values and can therefore be derived through rigorous probability , Get the state's estimate and uncertainty.

The fusion of motion information and observation information by probabilistic method is widely used in robot localization. The most typical one is based on the EKF-Localization [21] of Extended Kalman Filter (EKF) and Particle Filter PF-Localization) is also known as Monte Carlo Localization (MCL) [22]. Both of them are based on the assumption of no after-effect of Markov. According to the Bayesian formula, the probability distribution of the robot in the whole pose space is deduced. Because it is very difficult to directly solve the posterior probability distribution with the iterative formula, it can not be solved. Therefore, the probability distribution of the pose is simplified and approximated.

EKF localization simplifies the pose probability distribution to a Gaussian distribution, which can simplify the iteration formula of posterior probability greatly. The EKF localization algorithm is simple, efficient, fast, and real-time, but due to the single-mode nature of the Gaussian distribution, it is not possible to characterize the distribution of multiple hypotheses. EKF localization can not be handled if the robot is likely to be in multiple locations in the environment. The literature [23] proposes multi-hypothesis Kalman filtering and uses the hybrid Gaussian model to describe the robot pose distribution, which can solve the problem of environmental ambiguity to some extent. However, EKF localization can not be used for global localization and can only be used for pose tracking.

Monte Carlo localization uses the particle distribution in state space to characterize the probability distribution of pose states. The more dense the particles are, the higher the probability is, and the smaller the sparse probability is. In theory, as long as the number of particles is sufficiently large, the particle distribution can characterize any probability distribution and thus enable global localization. In addition, Monte Carlo localization can also handle the problem of kidnapping, and can recover autonomously in the event of a failure in localization. Moreover, by controlling the number of particles, the operation speed of particle filtering can be flexibly adjusted. As a result, MCL has become the mainstream algorithm for robot self-localization.

However, the classic MCL algorithm also has many problems such as large number of particles, large amount of computation, and particle degradation. For these problems, researchers have made many improvements. Fox [24] proposed a KLD (Kullback-Leiblerdistance) sampling algorithm that dynamically adjusts the number of resampled particles by calculating the KL distance of neighboring pose estimates. When particles are concentrated, they can effectively reduce the number of particles. Grisetti [25] proposed a self-adaptive resampling strategy for particle degeneracy and other problems, reducing re-sampling times and performing selective resampling, which can not only prevent particle degradation caused by oversampling, but also improve the speed of particle filter algorithms. Thrun

[26] proposed the inverse MCL, firstly used the observation model to estimate the pose, then used the motion model to evaluate the importance of the particles, and merged the conventional MCL and the backward MCL, which effectively improved the localization performance of the MCL.

In the localization algorithm, the observation modeling of robot observation and map matching is very important. The map description and observation model are the research hotspots in the field of localization and map construction. The two-dimensional map of the robot shows a topological map [27], a geometric feature map [28], and a probability map [29]. Among them, the probability grid map is the most widely used. The map model divides the environment into a series of two-dimensional grids, and each grid stores the probability that the cell is occupied by obstacles. For large-scale environments, the storage capacity of grid maps is relatively large. To address this issue, the paper [30] proposed a Multiple Representation Independent Evidence Log (MURIEL) grid map representation to effectively reduce the map size. The literature [31] uses a quadtree grid to simplify the map, and it works well in a local high-density environment. Probabilistic grid maps can describe the uncertainty of data and models, facilitate the fusion of multi-sensor information in the framework of probability, maps are easy to understand and handle, and can be easily used for navigation of robots, road planning, and obstacle avoidance. Today, the idea of such a probability grid is still the mainstream of self-localization.

3.3.3 Three-dimensional map localization method

With the development of sensing technologies such as 3D laser scanners and RGB-D cameras, researchers have begun to shift from 2D maps to the 6DoF localization of robots in 3D maps. In the three-dimensional map localization, the localization methods vary greatly depending on the sensor data, which can be mainly classified into the following three categories: One is a localization method based on a point cloud, and a 3D point cloud data is acquired by a 3D laser distance meter to perform localization; The other type is a vision-based localization method that obtains image data for self-localization through a monocular or binocular vision system. The third type is based on the localization of RGB-D data. In recent years, the RGB-D camera represented by Kinect was Widely used in the field of robot localization and map construction, RGB-D cameras integrate depth images and RGB images. Depth graphics can be converted into point cloud data, which is equivalent to the combination of point clouds and image data. The information is very rich.

Point cloud-based self-localization method usually through the registration of point cloud data to achieve posture tracking. The most commonly used point cloud registration algorithms are ICP (Iterative Closest Pomt) [32], NDT (Normal Distribution Transform) [33]; [34]. ICP is gradually registered by iteratively searching for neighboring points and matching corresponding point pairs. The registration accuracy is high but it is time consuming. The literature[35] optimizes the neighbor search by KD tree (K-dimensional search tree), but the search of massive point clouds still It is the bottleneck of the algorithm. In addition, the ICP algorithm requires a very high initial pose, and the initial pose is inaccurate. This can cause the ICP to fall into a local extreme. Usually, odometry information is needed as the initial value. The NDT algorithm models point cloud data as a series of normal distributions. It uses coarse-grained grids or octrees to simplify point clouds, and estimates the Gaussian distribution of the grid based on the point clouds in the grid. Simplification and segmentation smoothing. The NDT algorithm does not need to perform near-neighbor search. By performing pose optimization for optimization, the NDT algorithm can achieve the same accuracy as the ICP, but it also depends on the initial pose. The method of plane registration was proposed in [36]. Firstly, the plane block was extracted as feature in the point cloud data, and then registration was achieved through plane feature matching. The method can achieve global registration, and even though the initial pose varies greatly, there is still a good registration effect.

Among the visual self-localization methods, one uses binocular stereo vision [37], utilizes epipolar geometry for 3D restoration, and performs tracking and registration by means of image registration. The other uses a monocular camera via Structure From Motion. Techniques such as (SFM) [38]

recover three-dimensional information from video streams. Both methods use an image registration algorithm that matches the images of two adjacent frames to estimate the motion of the robot, commonly referred to as a visual odometer.

The research of visual odometer (VO) is very popular and many VO algorithms have emerged. Klein [39] proposed PTAM (Parallel Tracking And Mapping), which extracts feature points in the image and performs 3D restoration of feature points based on multi-frame observations to obtain feature maps. Then, it relies on feature maps to achieve localization. PTAM provides two threads. Tracking and Mapping were separately performed to implement a real-time SLAM system. Bemd [40] implemented monocular and binocular vision odometer based on sparse feature matching framework and established open source project LibViso, which is used by a large number of researchers. LibViso uses Harris corner as the feature point and features association through RANSAC. The point method for pose estimation has achieved good results in the KITTI dataset [41]. Howard [42] replaces RANSAC with the method of consistency constraint graph, transforms the feature association into the maximum group search problem of the constraint graph, and provides a new idea for feature association.

Comport [43] et al. first applied the Dense registration method to the binocular vision system. After that, Steinbrucker [44] proposed a similar Dense Odometry and applied this method to monocular VO. DenseVO's idea is to make use of the assumption of pixel consistency in the case of small offsets of the image. By optimizing the motion of the camera, the difference between the pixel values of the two images is minimized. Among them, Steinbrucker defines a deformation function to map a pixel in the source image to the target image, builds the energy function by using the mapped pixel difference, and uses the nonlinear optimization to obtain the optimal rigid transformation so that the source image is mapped to the target image With pixel consistency, the results show that under small camera motion, the registration accuracy is no less than the highest registration accuracy of the ICP algorithm, and the registration speed is higher than the ICP. Kerl[45] has performed stochastic modeling of Steinbrucker's algorithm and enabled it to integrate prior information such as IMU and odometer, which improves the robustness of the algorithm to a certain extent and can achieve 30HZ processing speed on the CPU. Real time is very strong.

In the past two years, many VSLAM algorithms have been proposed, of which the most prominent ones are LSD-SLAM [46] and ORB-SLAM [47] [48]. Both are based on monocular cameras for constructing 3D environmental maps and self-localization. Has achieved a very good map construction effect. LSD-SLAM (Large-scale direct monocular SLAM) does not extract sparse features but uses Dense registration method to directly use camera pixels for image tracking. In tracking, SLAM and map images The pose constraint diagram of the key frame indicates that the 3D point cloud model is recovered according to the key frame and its corresponding pose.ORB-SLAM is based on sparse feature matching method. It uses ORB as image feature, and ORB has rotation and scale invariance. , And do not need to rely on the GPU can have high real-time.ORB-SLAM system is similar to PTAM, also has Tracking and Mapping thread, the difference is that ORB-SLAM join LoopClosing (closed-loop detection) thread, based on Bag-of- Word (bag model) for scene recognition [49] for closed-loop detection and relocation.

Due to a series of advantages, Kinect and other RGB-D cameras have also been researched and applied in robot localization and map construction. Among them, KinectFusion [50] developed by Microsoft, can well track the camera and build a precise environment model. KinectFusion relies solely on depth information to accelerate the ICP algorithm through the GPU, realizing high real-time tracking and up to a processing speed of nearly 100 Hz. In addition, it uses the Trunced Signed Distance Function (TSDF) [51] to fuse the noisy Kinect point cloud, which can generate the Meah map with high accuracy and track the TSDF model to obtain the predicted surface of a given observation point , And then the surface and the actual observation point cloud registration, compared to frame to frame registration, a substantial increase in accuracy. However, KinectFusion consumes a lot of space and can only be operated in a small area (5 x 5m). Document [52] improved the TSDF model in

KinectFusion to dynamically adjust the environment described by TSDF to enable it to operate in a wide range of environments.

Since Kinect has RGB and depth information at the same time, the localization based on Kinect can fuse image registration and point cloud registration methods to achieve higher accuracy. Peter[53] registered the ICP and sparse features and used it to construct maps using Kinect's RGB-D data. He initially registers the RGB-D data with sparse features, and then uses ICP to achieve accurate registration. In the ICP optimization function, the reprojection error term of the feature registration is added, and the distance and correspondence of corresponding points are optimized at the same time. Reprojection error of the feature. This method uses both texture information (RGB) and geometric shape information (depth), and it has strong robustness. Whelan et al. [54] attempted a variety of fusion methods such as sparse features, ICP, Dense features, ICP, sparse features and Dense features, sparse features plus Dense features plus ICP. The experimental results show that the fusion of ICP and Dense features can achieve The best registration effect.

The observation model in three-dimensional localization usually has large space consumption. For example, the memory cost of a three-dimensional grid map is much larger than that of a two-dimensional grid map. In order to be able to position-correct Kinect pose-based pose correction according to the observed model, Biswas [55] projected the 3D data onto a 2D ground and then corrected the pose using a 2D map model. However, this method requires that the Kinect field must have ground, Otherwise it cannot be projected. Ito [56] also converted 3D data to 2D, but instead of projecting to the ground, it used Kalect's elevation angle to intercept wall data from a certain height on the ground for localization. However, the accurate estimation of Kinect's pitch angle is in this method. The difficulty.

In the three-dimensional localization by Kinect, MIT's Fallon [57] et al. established a plane CAD model by extracting the plane in the map. When performing pose estimation, similarly, ray tracing is used to predict depth observations, similarity is calculated with the actual depth image, and then localization is performed based on similarity through Monte Carlo localization. The CAD model is very streamlined and can be used to map a large environment and meet the real-time requirements. However, the method based on the plane limits its application environment can only be confined to a plane rich structured environment.

3.3.4 route plan

The path planning of mobile robots is based on the robot's perception of environmental information by its own sensors, self-planning of a safe operation route, and efficient completion of job tasks. From the specific algorithm and strategy of path planning for mobile robots, the path planning technology can be summarized into four categories: template matching path planning technology, artificial potential field path planning technology, map construction path planning technology and artificial intelligence path planning technology.

(1) Template matching path planning technology

The template matching method compares the current state of the robot with the past experience, finds the closest state, and modifies the path in this state to obtain a new path. That is, firstly, a template library is established by using or generated information of the path planning, and any template in the library contains environment information and path information of each planning which can be obtained through a specific index; then, the current planning task and The environmental information is matched with the template in the template library to find an optimal matching template; then the template is modified and used as the final result. The template matching path planning method has a simple principle and works well when the matching is successful. However, the fatal flaw of this method is that it depends on the robot's past experience. If there is not enough path templates in the case base, it may not find a path that matches the current state. At the same time, this method mainly focuses on the path planning of static environment. Change, it is more difficult to find a matching path template. These deficiencies severely limit the in-depth research and popularization of template matching path

planning techniques, so template matching should have enough matching cases (paths) and adaptability to environmental changes.

(2) Artificial Potential Path Planning Technology

The basic idea of the artificial potential field path planning technology is to regard the movement of the robot in the environment as a kind of robot movement in a virtual artificial force field. Obstacles generate repulsive force on the robot, and the target point generates gravitational force by the robot, and the combined force of gravity and repulsion acts as the control force of the robot to control the robot to avoid the obstacle and reach the target position. The early artificial potential field path planning research is an artificial potential field in a static environment, that is, both the obstacle and the target object are regarded as static and invariable. Robots plan motion paths based only on the specific locations of obstacles and targets in a static environment, regardless of their speed of movement. However, the environment in the real world is often dynamic, and both obstacles and targets may be mobile. Therefore, path planning in the dynamic environment is the most important solution to the problem.

(3) Map Construction Path Planning Technology

Map construction path planning technology, according to the robot's own sensor search for the obstacle information, the robot surrounding area is divided into different grid space (such as free space and limited space, etc.), computing grid space obstacle occupancy, and then based on Certain rules determine the optimal path. Map construction is divided into signposting and gridding, also called cell decomposition method. The former is to construct a feasible path diagram of a robot consisting of landmark points and connecting edges, such as visual line method, tangent diagram method, Voronoi diagram method and probability graph expansion method.

(4) Artificial Intelligence Path Planning Technology

Artificial intelligence path planning technology is to apply modern artificial intelligence technology to the path planning of mobile robots, such as artificial neural network, evolutionary computation, fuzzy logic and information fusion. Genetic algorithm is the first intelligent optimization algorithm applied to the combinatorial optimization problem. The algorithm and its derivative algorithm have been applied in the field of robot path planning research. As an important part of artificial intelligence, neural networks have received extensive attention in the research of path planning for mobile robots. Artificial intelligence technology is applied to the path planning of mobile robots, which enhances the "intelligent" characteristics of the robot and overcomes the deficiencies of many traditional planning methods. However, this method also has some shortcomings. The genetic optimization and ant colony algorithm for path planning mainly focus on some problems in path planning, which are optimized by using evolutionary computation and combined with other path planning methods to accomplish the path planning task alone The situation is less. For neural network path planning, most neural network path planning has a learning process of planning knowledge. It is not only difficult to acquire the learning samples, but also has learning lag, which affects the real-time nature of neural network path planning. Although the bio-inspired neural network path planning is better in real-time, there are artificially uncertain factors in the setting of input incentive and suppression. At present, genetic algorithm and particle swarm algorithm have been applied to mature path planning algorithm. Fish swarm algorithm and fireflies algorithm are emerging swarm intelligence algorithms, which have great application prospects.

The above algorithms each have their own advantages and disadvantages. However, because AGV often has many unknown moving obstacles, ambulance staff or other AGVs in the working environment, it can ensure that the mobile robot has navigational obstacle avoidance in a dynamic unknown environment Ability is very necessary. In the dynamic unknown environment, the method of local path planning is generally used.

4. currently existing problems

Low-cost implementation and application of SLAM (real-time localization and map building) based on laser ranging sensor for AGV. At present, most AGVs in China mainly use laser guidance or magnetic guidance, and it is necessary to set the running trajectory in advance. Autonomous navigation AGV on the market mainly depends on imports from abroad, and there are few AGVs based on common laser rangefinders to achieve automatic map construction and real-time navigation at low cost. Therefore, this project intends to increase the SLAMTEC PRLIDAR laser sensor on the basis of the existing photo guide AGV in the laboratory, build a ros software platform, and achieve autonomous navigation of the AGV.

Robot's global localization problem. Integrated local localization and global localization are the functional requirements of autonomous navigation robots. However, most algorithms only solve the problem of local localization (position tracking). In recent years, the research of the global localization algorithm that emerged is mainly the Monte Carlo Localization (MCL) algorithm in probabilistic localization. Compared with other localization algorithms, it can describe multi-peak distributions, can approximate a wide range of probability distributions, and can use higher frequencies. Fusion measurement information has higher localization accuracy, but there are still problems of particle degradation, particle exhaustion, large amount of calculation, and poor real-time performance. Therefore, the key to solving the localization and navigation of mobile robots is to improve the Monte Carlo localization algorithm.

Path planning problem. Currently, A* algorithm and D* algorithm are suitable for global path planning and simple structured environments. They can not meet the requirements of path planning algorithm for accurate acquisition of environmental information, and their search optimization methods cause huge calculations and calculations. Time-consuming, limiting its performance in real-time decision-making. Genetic algorithms and particle swarm optimization have been successfully applied in solving

5. Conclusion

At present, the localization and navigation of mobile robots is a research hotspot in the field of robotics. It has important theoretical significance and practical value. A large number of scholars are conducting research and exploration in this area in order to expect real robot autonomy. This dissertation focuses on the navigation problems of mobile robots based on laser range finder, and summarizes its localization and navigation methods. The method of map construction, localization and path planning is introduced in detail. The SLAM method and probabilistic localization are mainly introduced. The method and artificial intelligence path planning technology have analyzed the Monte Carlo algorithm's high computational complexity, poor real-time performance, particle degradation, and the problem that the standard intelligent path planning method is slow in convergence and easy to fall into local optimum.

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