Artificial Intelligence Technologies and Applications
C. Chen (Ed.)

doi:10.3233/FAIA231288

A Method for Autonomous Shelf Recognition and Docking of Mobile Robots Based on 2D LiDAR

Yifan ZHAO, Xiang LI, Wei LU[1] and Lizhi HU
Zhejiang HuaRay Technology Co., Ltd., Hangzhou, China

Abstract. This paper presents a method for mobile robots to recognize and dock shelves based on 2D LiDAR, which can autonomously identify shelves and perform high-precision docking. A geometric feature-based shelf leg recognition and multi-shelf model screening method is designed, which can quickly and accurately autonomously identify shelves. A fitting method for the center of shelf legs and shelf centers based on nonlinear least squares was proposed, and a real-time autonomous docking system was designed, which can autonomously distinguish shelf size types and perform precise docking. The experiment shows that the proposed method can achieve a docking accuracy of ± 1 cm.

Keywords. Mobile robot, shelf identification, autonomous docking, positioning.

1. Introduction

Mobile robots are playing an increasingly important role in industries, logistics, and other fields, which include key technologies of target recognition and docking. In factories, mobile robots need to carry shelves for autonomously picking and delivering products, which requires precise identification of the relative position between the robot and the shelves. At present, the commonly used navigation algorithms for mobile robots, such as laser SLAM navigation, QR code navigation, inertial navigation, etc., are insufficient to provide the accuracy required for shelf recognition and docking. Shelves often have significant deviations from the coordinates on the map due to manual placement, collisions, etc. When docking according to the established position on the map, it is easy to cause serious losses due to collisions.

This paper proposes a method for autonomous recognition of shelf docking, which can improve the accuracy and stability of mobile robots docking shelves. The research results of this paper are as follows:

1). A 2D LiDAR-based autonomous shelf recognition and detection method is proposed, which utilizes geometric features and nonlinear optimization methods to locate the pose of shelves.

2). A method for autonomously identifying multiple shelf types has been proposed, which can quickly and accurately determine the type and size of shelves.

3). A real-time identification and autonomous path planning docking method has

[1] Corresponding author: Wei LU, Zhejiang HuaRay Technology Co., Ltd., Hangzhou, China; e-mai: lwhfh01@zju.edu.cn

been proposed to improve the accuracy and efficiency of shelf docking;

The second part summarizes the relevant work, and the third part introduces the relevant work of identifying and docking the system; The fourth part provides experimental data and analysis, while the fifth part summarizes the research in this paper.

2. Related Works

The robot target docking process can be divided into two stages, the approach stage and the autonomous docking stage [1]. During the approach phase, the robot uses inertial, laser, and other navigation methods to move in the working environment, reaches the switching area around the docking target, and enters the autonomous docking phase. Identifying and locating the target pose and planning a path can reach the designated location for docking. There are mainly laser navigation, visual navigation, and other methods for robot navigation, among which laser SLAM navigation has made rapid development in recent years. The cartographer algorithm proposed by Hess scans the map using a branch and bound algorithm to construct loop constraints and reduce the error of the laser odometry [2], [3], utilizes the extraction of geometric features from point clouds, and establishes constraints on feature points to solve pose problems. To increase the robustness of positioning, sensors such as IMU and wheel odometers are used to improve the accuracy and robustness of robot positioning [4].

With the increasingly widespread application of robots, various target recognition and docking methods have emerged. [5] determines the pose of the charging station relative to the robot by detecting ArUco markers based on the camera and using linear trajectory docking. [6] uses three low-cost sensors to detect different objects and achieve good detection accuracy. Compared to cameras, LiDAR has higher measurement accuracy and is not affected by lighting. [7] installs the LiDAR at the bottom of the forklift. [8] uses the LiDAR to detect and identify the position of the pallet and uses the feature matching method for pallet scanning. In addition, point cloud matching-based methods are also widely used. The ICP [9] method can calculate the pose of the detection target relative to the robot by minimizing the distance between two cloud points. [10] extracts 4 coplanar points as point pair features and uses affine invariance and maximum overlap rate of point sets to achieve point cloud matching. However, due to the sparsity of LiDAR data, the proportion of effective interior points is relatively small, making such methods highly challenging for shelf recognition. Therefore, this article proposes a shelf recognition method based on 2D LiDAR, which locates the pose of shelves by extracting geometric features.

3. Shelf Detection and Positioning Method Based on 2D LiDAR

Robots need to independently identify the size and type of shipping shelves. This paper defines the length and width of the shelf legs of the shelf model as G_h, G_w, and the shelf length as L and width as W, and defaults to the orientation of the longer side of the shelf as the orientation of the shelf. We use L, B, and M to represent the coordinate frame of LiDAR, robot, and global map, respectively. The calculation of laser points in the following text is based on this coordinate system. After identifying and obtaining the coordinates of the shelf center, it is converted to M and the docking process is executed.

3.1. Laser Data Preprocessing

At the scanning plane height of the LiDAR, the initial point cloud is processed to obtain the point cloud near the shelf legs. Point cloud filtering is based on distance, and filtering points outside circular areas are centered around the preset shelf center, denoted by R*γ (R is the length multiple of the longest diagonal in the shelf model, γ Is a coefficient). We calculate the distance between adjacent points and cluster points if the distance is small enough. Due to factors such as material shape and reflectivity, laser data may exhibit outliers such as trailing points, which can affect the recognition of shelf legs. Therefore, after obtaining *n* clustered point cloud clusters $P\{P_0, P_1, \ldots, P_n\}$, it is necessary to remove trailing point clouds from each point cloud cluster.

This paper filters trailing points by comparing angles between adjacent points in the same point cloud cluster. As shown in Figure 1, assuming the origin of the radar is *O* and the two adjacent points *A* and *B* in the *i*-th point cloud cluster P_i, the included angle β can be calculated:

$$\beta = \tan^{-1}\frac{OB*\sin\alpha}{OA-OB*cos\alpha} \quad (1)$$

The angle α between adjacent points is the angular resolution of LiDAR. When the angle β is too small, we remove point A which is too far away. We further filter based on the length and number of points of the point cloud cluster, retain point cloud clusters that are similar in size to the shelf legs, and define them as candidate point cloud clusters. As shown in Figure 2, after preprocessing, a large number of invalid points were filtered and successfully removed from the shelf trailing point cloud.

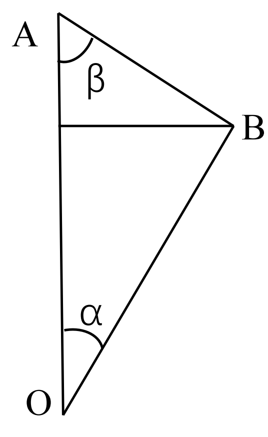


Figure 1. Trailing point cloud filtering schematic diagram

3.2. Shelf Recognition Based on Geometric Features

It is difficult to identify shelves using only the information of a single point cloud cluster, so this article focuses on the geometric relationships between point cloud clusters. Due to the four shelf legs forming a rectangle, it is possible to identify shelves by determining whether the centers of the four shelf legs meet the geometric features of the rectangle.

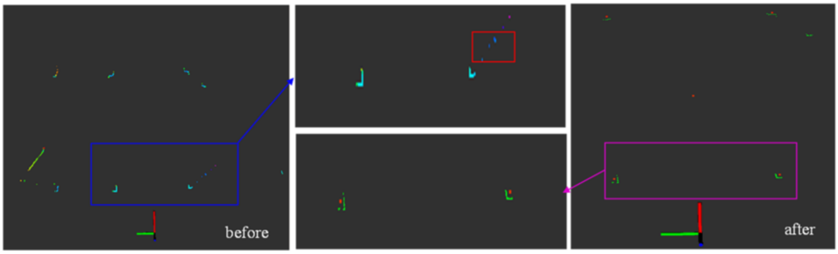


Figure 2. Comparison of shelf legs before and after fitting

We calculate the mean coordinates of each point cloud cluster as the center point of the point cloud cluster and select the point set that meets the conditions in the point cloud cluster. We take the pruning operation shown in Figure 3 to reduce search time. The criteria for pruning are as follows: 1). Determining whether the length of the line segment composed of two points is appropriate; 2). Calculating whether the triangle composed of three points approximately satisfies the Pythagorean theorem; 3) Any three of the four points must be able to form a right triangle.

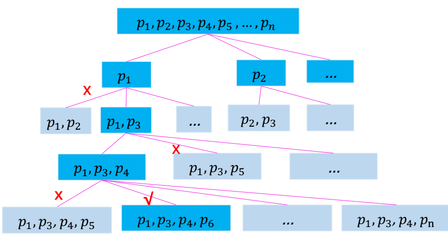


Figure 3. Schematic diagram of search pruning

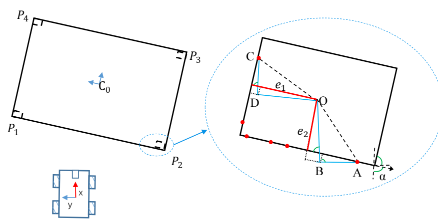


Figure 4. Schematic diagram of shelf leg fitting

After the above search, a set of candidate shelf leg points that match rectangular features can be obtained. Due to the laser resolution, shelf material size, and shelf placement angle, four-shelf legs that meet the conditions cannot be obtained, so three points that meet the characteristics of the right triangle are selected as candidate shelf leg point sets.

After the above search, one or more point sets that match the geometric features of the shelf are obtained, and further judgment is made on the shelf model that matches these point sets. We calculate the side length of the rectangle or right triangle formed by the above point set, compare it with the given dimensions of multiple shelf models according to Equation 2, and select the models with smaller errors.

$$\begin{cases} \mathrm{err_L} = |l_k - \mathrm{L}_i| < \gamma_L \\ \mathrm{err_w} = |w_k - \mathrm{W}_i| < \gamma_w \\ \mathrm{err_{sum}} = \mathrm{err_L} + \mathrm{err_w} < \gamma_{sum} \end{cases} \tag{2}$$

L_i, W_i is the length and width of the i-th shelf model, l_k, w_k is the average value of the long and wide edges of the k-th point set, respectively, and $\gamma_L, \gamma_w, \gamma_{sum}$ is the corresponding error threshold. Now, we obtain modules M that match the point set P (p_1, p_2, p_3, p_4) and call it a points-model pair, such as $\{P, M\}$. When multiple points-model pairs meet the conditions, we choose the model M_{best} which has smaller $\mathrm{err_{sum}}$. We calculate the distance between M_{best}'s $\mathrm{err_{sum}}$ and others and only save the points-model pair with differences less than λ cm.

3.3. Fitting of Shelf Legs

Accurately fitting the center of the shelf legs is based on the shelf model. Based on the identified center point of the shelf leg, we obtain the corresponding filtered point cloud cluster in 3.1 and use the principal component analysis (PCA) method to calculate the main direction of the point cloud cluster by calculating the eigenvalues of the point cloud distribution. For the i-th point cloud cluster P_i with *N* points, we calculate its centroid P_{ci} from the following point cloud distribution matrix equation:

$$\mathrm{P}_{ci} = \frac{1}{N}\sum_{j=1}^{N} p_j \tag{3}$$

$$\xi_i = \frac{1}{N}\sum_{j=1}^{N}\left(p_j - \mathrm{P}_{ci}\right)^T\left(p_j - \mathrm{P}_{ci}\right) \tag{4}$$

We use SVD decomposition to obtain a matrix ξ_i, whose maximum eigenvalues correspond to the main direction β of the cluster point cloud. Then we use a nonlinear least squares method to fit and solve the coordinates of the center $P_O(p_{ox}, p_{oy})$ of the shelf legs. As shown in Figure 4, point $A(\mathrm{p}_x, \mathrm{p}_y)$ is a laser point hit on the shelf leg, defined as α to determine the orientation of the shelf legs and the components of the straight line *OA* in the LiDAR coordinate system can be obtained. Based on the geometric relationship, a residual function e_2 can be established. Similarly, we construct a residual function e_1 for point C:

$$\begin{cases} e_1 = \left| |p_x - p_{ox}| \cos\alpha + \left|p_y - p_{oy}\right| \sin\alpha - \frac{G_h}{2} \right| \\ e_2 = \left| |p_x - p_{ox}| \sin\alpha - \left|p_y - p_{oy}\right| \cos\alpha - \frac{G_w}{2} \right| \end{cases} \tag{5}$$

The residual functions constructed by laser hitting different edges of the shelf legs are different. This paper calculates the residual e_1, e_2 separately and takes the minimum value as the residual function for that point. If the shelf legs are circular, we construct a residual function as shown in Equation 7, which is combined with Equation 6 to obtain the center coordinates of the shelf legs.

$$f(p_o, \alpha) = \sum_{i=1}^{n} \|err_i\|^2 \tag{6}$$

$$err = \left| (p_x - p_{ox})^2 + \left(p_y - p_{oy}\right)^2 - \frac{\mathrm{l}_h}{2} \right| \tag{7}$$

We solve Equation 6 to calculate the pose of the center of the shelf leg and update the coordinates of the corresponding point cloud points. As shown in Figure 2, the red dots in the point cloud cluster represent the center of the shelf leg calculated by fitting, which can accurately fit the position of the center of the shelf leg.

3.4. Positioning of Shelf Center

Assuming the point set of model pairs is $\{p_1, p_2, p_3, p_4\}$as shown in Figure 4, the initial value of the corresponding shelf center C_0 is obtained from the mean of four point sets, the initial orientation of the shelves should be the direction of $L_{p_2p_3}$ or $L_{p_1p_4}$, and then we establish the corresponding residual function. Taking point p_1 as an example, we construct the error equation regarding the center and orientation $C(c_x, c_y, c_\alpha)$ of the shelf as follows:

$$u_{0x} = c_x - \cos c_\alpha * \frac{L}{2} + \sin c_\alpha * \frac{W}{2} \tag{8}$$

$$u_{0y} = c_y - \sin c_\alpha * \frac{L}{2} - \cos c_\alpha * \frac{W}{2} \tag{9}$$

where L and W are the edge lengths of the model corresponding to the edges $L_{p_1p_4}$ and $L_{p_1p_2}$, respectively. Then the corresponding error term is:

$$e_0 = |p_{1x} - u_{0x}| + |p_{1y} - u_{0y}| \tag{10}$$

$$f(C) = \sum_{i=0}^{n} e_0. \tag{11}$$

Similarly, the error term of the remaining shelf legs of the frame. As shown in Equation 11, we establish a nonlinear least squares problem about the center of the shelf and iteratively solve it, where n (n=3,4) is the number of shelf legs. When there are multiple point set model pairs, we calculate the distance between the fitted shelf center and the preset shelf center, select the one with the smallest distance as the shelf center C (c_x, c_y, c_α) for this recognition, and further project this result using external parameters and the current pose of the robot onto the map coordinate system M.

3.5. System of Docking

The docking process of this article is divided into the approaching stage and the automatic docking stage. In the approach phase, a laser SLAM-based navigation method is used to approach the target along the established route, and the paper adopts inertial navigation mode after entering the automatic docking phase.

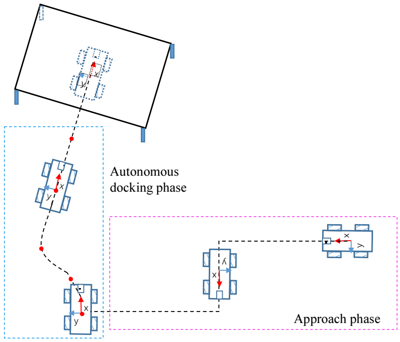


Figure 5. Schematic diagram of the target docking system

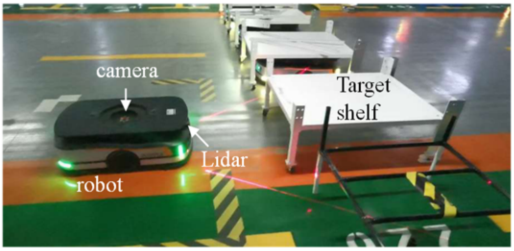


Figure 6. Robot docking shelf diagram

To improve the robustness and efficiency of recognition docking, multiple shelf recognition will be conducted during the mobile docking phase as shown in Figure 5, and the deviation value between each recognition result p (x_0,y_0,θ_0) and the current path planning endpoint $P(x,y,\theta)$ (using the preset shelf center coordinates and orientation for the first time) will be compared. When the deviation value exceeds the threshold, the coordinates of the docking target are updated and the path is re-planned to select the optimal recognition result.

The paper uses a QR code posted in the center position below the shelf as verification information, and the robot drives to the bottom of the shelf according to the recognition results. When approaching the recognizing position, we turn on the overhead camera installed in the center of the robot body in advance, scan, and search for the QR code below the shelf. If the camera detects that the pose relative to the QR code exceeds a certain threshold, we adjust the position of the device to meet the accuracy requirements and then lift the shelf to complete the shelf recognition docking.

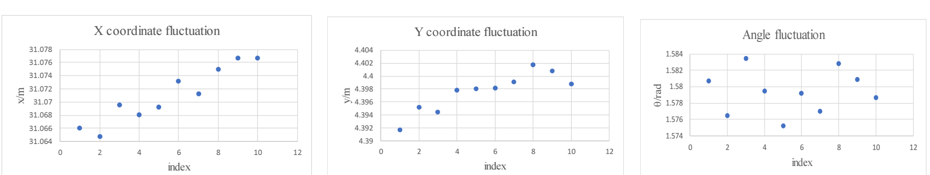
4. Experimental Evaluation

This paper uses IRAYPLE AMR4.0 equipment for testing, as shown in Figure 6. The equipment is equipped with VANJEE 716 LiDAR with an angular resolution of 0.33°. The first experiment tested the matching degree between the shelf size fitted by the algorithm and the shelf model. The robot was positioned at a certain distance in front of the shelf, ensuring that the radar was about 0.5 m away from the legs of the shelf in front of the shelf. Multiple recognitions were conducted and the size of the fitted shelf was calculated as shown in Table 1. The error of the fitted shelf size was between 0.3% and 4.1%, indicating good recognition accuracy.

Table 1. Matching accuracy of shelf model

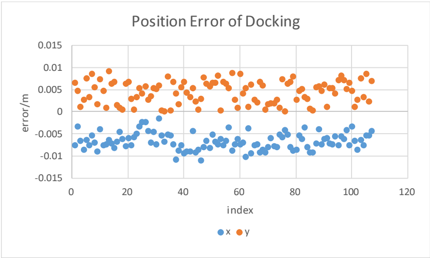
	Shelf model					Size of fitted shelves			
Index	Shelf leg type	Shelf length /m	Shelf width /m	Shelf leg length /m	Shelf leg width /m	Shelf length /m	Shelf width/m	The error of Shelf length	The error of Shelf width
1.	Circular	0.90	0.81	0.026	0.026	0.903	0.8239	0.3%	1.7%
2.	Rectangle	1.075	0.883	0.04	0.04	1.0801	0.9194	0.47%	4.1%
3.	Rectangle	1.25	1.25	0.04	0.04	1.2569	1.2859	0.55%	2.3%
4	Rectangle	1.08	0.856	0.04	0.04	1.1122	0.8452	3%	1.3%

As shown in Figure 7, the fluctuation of the recognition results of multiple shelf recognition by the robot during a single automatic docking stage was statistically analyzed. Ten recognition attempts were made during this docking, with fluctuations in the x coordinate, y coordinate, and angle being 0.0119 m, 0.0010 m, and 0.0081 rad, respectively. In a single recognition process, this algorithm can achieve relatively small fluctuations in recognition results at different recognition distances and good stability.

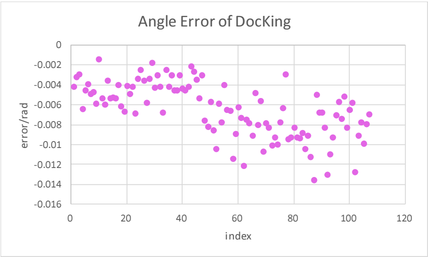


(a) (b) (c)

Figure 7. Fluctuation of recognition results



(a)



(b)

Figure 8. Docking accuracy

This paper uses the offset of the shelf relative to the vehicle body obtained by the camera's detection of the QR code after docking to identify the deviation between the docking result and the actual value. Figure 8 shows the docking errors of a robot docked multiple times to the same shelf. The docking errors of positions including x and y coordinates are all within 1 cm, and the docking errors of angles are within 0.014 rad, which can meet the actual docking accuracy requirements. In addition, in the autonomous docking area (starting point of identifying the shelf position), we move at a speed of approximately 0.4 m/s for a distance of about 4.5 m and calculate the time taken from entering the area to completing the docking shelf (shelf 2 in Table 1). The method proposed in this article takes an average of 11.21 seconds, while the method of setting a parking spot in front of the shelf for recognition takes an average of 15.138 seconds. This method can reduce time consumption by 25.9% and has higher operational efficiency. In addition, improper installation of Lidar can easily lead to recognition failure due to inclination angle. Therefore, if the recognition is only done once, the risk of failure is high. The method proposed in this paper identifies multiple times during the docking phase, improving the robustness and success rate of the docking.

5. Conclusion

In this paper, a method for mobile robot recognition and docking of shelves based on 2D LiDAR is proposed. A shelf leg recognition strategy and a multi-shelf model screening strategy are designed, which can quickly and accurately autonomously identify shelf types. A fitting method was proposed for the center of the shelf legs and the center of the shelf, and models were used to accurately locate the center of the shelves. We have designed a real-time autonomous docking system that can perform precise docking. The experiment shows that this article has good fitting accuracy for shelves, and the recognition results are relatively stable, ensuring a position accuracy of ± 1 cm and an angle accuracy of 0.014 rad. It has good docking accuracy and efficiency. The method proposed in this paper improves the docking accuracy and intelligence level of mobile robots and has good application value.

References

[1] Wang. J, Shan. M, Yue. Y, and Wang. D.(2021) Autonomous target docking of nonholonomic mobile robots using relative pose measurements. IEEE Transactions on Industrial Electronics, 68(8): 7233-7243.

https://doi.org/10.1109/TIE.2020.3001805.
[2] Hess. W, Kohler. W, Rapp. H, and Andor. D. (2016) Real-time loop closure in 2D lidar slam, In: IEEE International Conference on Robotics and Automation, Stockholm, Sweden, pp. 1271-1278.https://doi.org/10.1109/ICRA.2016.7487258
[3] Zhang. J, and Singh. S. (2017) Low-drift and real-time lidar odometry and mapping. Autonomous Robots, 41(2):401-416. https://doi.org/10.1007/s10514-016-9548-2
[4] Shan. T, Englot. B, Meyers. D, et al. (2020) Lio-sam: tightly-coupled lidar inertial odometry via smoothing and mapping.In: IEEE/RSJ international conference on intelligent robots and systems, IEEE. pp. 5135-5142. https://doi.org/10.1109/IROS45743.2020.9341176
[5] Romanov, A. M. and Tararin, A. A. (2021) An automatic docking system for wheeled mobile robots. In: 2021 IEEE Conference of Russian Young Researchers in Electrical and Electronic Engineering (ElConRus). IEEE.pp:1040-1045. https://doi.org/ 10.1109/ElConRus51938.2021.9396509
[6] Martin. J, Fink. T, May. S, et al. (2017) An autonomous transport vehicle in an existing manufacturing facility with a focus on the docking maneuver task. In: 3rd International Conference on Control, Automation and Robotics (ICCAR). IEEE, 2017. pp.365-370. https://doi.org/10.1109/ICCAR.2017.7942719
[7] Gao. L, Yuan. P, Wang. T, et al. (2016) Automatic recognition about pallets based on tracking algorithm of lidar and SLAM. In: International Conference on Advanced Robotics & Mechatronics. IEEE.pp. 196-201. https://doi.org/10.1109/ICARM.2016.7606918
[8] He. Z, Wang. Y and Hong. Y. (2011) Feature-to-feature based laser scan matching in polar coordinates with application to pallet recognition. Elsevier Ltd. Elsevier Ltd.15:4800-4804. https://doi.org/10.1016/j.proeng.2011.08.897
[9] Besl P.J.(1992) A method for registration of 3d shapes. IEEE Trans on PAMI, 1611: 586-606. https://doi.org/10.1117/12.57955.
[10] Mellado. N, Aiger. D and Mitra. N. J. (2015)Super4pcs: fast global point-cloud registration via smart indexing. Computer Graphics Forum, 33(5):205-215.https://doi.org/10.1145/1399504.1360684