Research Article

Lidar Based Position Estimation in Warehouse Logistics

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Abstract

This study introduces a lidar-based algorithm developed to overcome the difficulties encountered in localizing autonomous robots in complex environments. The testing procedure involves identifying lines coming from points, determining the intersections of these lines, and then calculating the location. The location calculation process was carried out by comparing the instantly obtained intersection points with the previous intersection points. The results obtained from the developed algorithm serve to explain the practical application of the algorithm and demonstrate its ability to achieve precise location detection in real-world scenarios. The findings highlight the effectiveness of the algorithm and its potential to contribute to the advancement of autonomous robot navigation in complex environments.

Keywords: *Localization, Odometry, Pose estimation, Lidar, Intersection Points*

1. Introduction

Localization of autonomous robots refers to the process of determining the position of a robot within its environment. This process is performed using sensor data by detecting objects around the robot or using various localization techniques. Localization is a fundamental ability for robots to perform various tasks, overcome obstacles, and accurately target objects with which they will interact. This process includes the integration of complex mathematical algorithms, artificial intelligence and sensors. It is also an important element to ensure that autonomous robots move reliably and precisely. For these reasons, localization is one of the most important issues to be solved in mobile robots.

Liu and her colleagues fused odometry and IMU (Inertial Measurement Unit) data with the EKF (Extended Kalman Filter) filter. They also used the fused data to the AMCL

(Adaptive Monte Carlo Localization) algorithm to find the initial location of the vehicle according to the map. Thus, they localized the robot using the AMCL algorithm with filtered data [1]. Vasiljević and his colleagues compared the real data they measured with lidar and the virtual measurement values that would occur at the predicted point according to the map, using the Discrete Fourier transform. By performing this analysis method several times, they ensured the localization and precision of the vehicle [2]. Zhang and Singh used visual odometry and lidar odometry. They created maps by combining these two data. They conducted many tests by changing multiple cameras and vehicle speeds and presented the test results [3]. Javanmardi and his colleagues presented the use of 2D vector maps for localization with Lidar. With this method, they saved the space occupied by 3D maps. They tested their method by providing a more precise localization performance than conventional 2D maps [4]. Wolcott and colleagues provided Lidar localization using the Gaussian Mixture method. In a 2D map, each cell maintains a Gaussian mixture one-dimensional model that models the distribution of the height Z of this cell [5]. Wang and her colleagues extracted edge and planar features from lidar scanning data and created a local edge map and local plane map. They offer a localization algorithm by estimating the most appropriate position between the data received from lidar and the map [6]. Zhang and his colleagues used 2D lidar that can move in 6 axes. They obtained a 3D point cloud using this lidar and used it in their algorithms. The methodology they propose uses two different algorithms. The first operates at high frequencies and low accuracy. The other one works with high accuracy at low frequency. They create location data by comparing edge points and planar points in the lidar cloud [7]. Zheng and Zhu carried out a study on eliminating lidar data coming in parallel with the location that is not effective in localizing 3D Lidars. With the data they obtained, they made position estimation using the rolling closest point method, the bird's eye view method and the range adaptive method [8]. Belkin and colleagues present a modular approach to lidar-based localization by combining A-LeGO-LOAM, Interactive SLAM and Localization with batch scan processing methods to achieve high precision. A new procedure based on the modified Monte Carlo localization method is proposed to evaluate the robot's initial position, and a study is conducted on the effect of errors in initial position estimation on real-time positioning convergence [9]. Yin and colleagues focus on recent advances in LiDAR-based global localization. In his work, he formulates the problem of pose estimation and indicates its scope of application and examines the latest developments in various aspects of the methodology. In his work, he formulates the problem of pose estimation and indicates its scope of application and examines the latest developments in various aspects of the methodology. They carried out their research under three headings: combining global location access and local pose estimation, upgrading one-time measurements to sequential measurements for

sequential global localization, and extending single-robot global localization in multi-robot systems [10].

The main contribution of this article is that, instead of using the ICP (Iterative Closest Point) method as used in the literature, a different study is included into thought during the position calculation process. In the study, the changes of the lines were examined using a vector methodology and the position calculation was carried out by processing the data obtained from the point cloud. This vector approach with the original algorithm developed has increased the performance of the system by offering a different perspective to the positioning process.

This paper is organized as follows: In Section 2, describes the developed methodology in detail. Additionally, position estimation by obtaining lines and determining intersection points using Lidar data is presented in this section. The results of the study are given in Section 3.

2. Materials and Methods

For autonomous mobile robots, localization means the ability to accurately determine their location in their environment, and this ability determines the precision with which the robot approaches the target point. At the same time, good location accuracy allows the robot to better follow the path it needs to follow in path planning. If the localization accuracy of a robot is low or incorrect, many negative situations may occur, such as the robot hitting obstacles, getting stuck, or going to the wrong targets. For these reasons, localization has an important place for mobile robots.

In this study, a 2D Lidar was used to calculate the robot position. Point cloud data obtained from lidar was used to localize the robot. In the method used, instead of creating location data by comparing points, lines were created with these points and location data was obtained by comparing the points where these lines intersect.

2.1. Equations of Line

While obtaining lines from lidar data, all points are scanned. Points whose directions are close to each other are grouped. Thus, the points that will form the lines are determined.

In the grouping stage of points, all points are scanned sequentially and the derivative values between each point and the previous point are calculated. Points whose direction

changes based on their derivative values are not included in the group. In Equation 1, the derivative value between the point and the previous point is calculated.

$$f'(x) = \frac{(x_i - x_{i-1})}{(y_i - y_{i-1})} \tag{1}$$

The function in Equation 2 is used to make line calculations from the grouped points.

$$y_i = a + bx_i \tag{2}$$

$$a = \frac{\sum_0^n y - b \sum_0^n x}{n} \tag{3}$$

$$b = \frac{(n \sum_0^n x_i y_i - \sum_0^n y \sum_0^n x)}{n \sum_0^n x^2} - \left(\sum_0^n x\right)^2 \tag{4}$$

How close the calculated lines are to the points is a critical factor in determining the precision of a system or model. Having these lines as close to the data points as possible increases the accuracy of the system or model. In this context, the least squares method was used to determine the **a** and **b** parameters of the function given in Equation 2. The functions of the least squares method are given in Equations 3 and 4.

The method of the lowest squares is to calculate the parameters of the line in a way that minimizes errors in the data points. As a result, as the line passes over the data points, it is adjusted to minimize the total number of squares of distances to these points. This ensures that the line best reflects the variability in the data set and increases its generalization ability.

2.2. Calculation of Intersection Points

Intersection points represent important reference points within the system. The functions of ordered lines are shown in Equations 5 and 6. The intersection point obtained from these functions changes dynamically depending on the movement of the robot. Therefore, intersection points are of critical importance in determining the robot's position.

$$y_{i-1} = a_{i-1} + b_{i-1} x_{i-1} \tag{5}$$

$$y_i = a_i + b_i x_i \tag{6}$$

Dynamic change occurs due to the displacement of intersection points depending on the movement of the robot. This is important for updating the robot's position and adapting it to changing conditions in its environment. Therefore, accurately identifying and constantly updating intersection points helps optimize the system performance by increasing the robot's accuracy in the localization process.

When two lines intersect, the x and y coordinates of these lines must be equal to each other, as shown in Equation 7. Using this equation, the location of the intersection point at x_i is calculated as in Equation 8. If the values of b_i and b_{i-1} are equal to each other, the lines are parallel to each other and do not intersect.

$$\begin{aligned} x_{i-1} &= x_i \\ y_{i-1} &= y_i \end{aligned} \tag{7}$$

$$x_i = \frac{(a_{i-1} - a_i)}{(b_i - b_{i-1})} \tag{8}$$

From the equation in Equation 8, the location of the intersection point x_i is calculated as in Equation 9. If b_i and b_{i-1} values are equal to each other, the lines are parallel to each other and do not intersect.

2.3. Estimation of Robot Position

The movement of the robot is a complex process that can include both linear and angular displacements. The vector representing angular displacement is the part of the intersection point perpendicular to the line to the center. The rotation vector shows changes in the orientation of the robot during its movement. On the other hand, linear displacement vectors indicate that the change at any point of the robot is in the same direction. This means that the robot travels the same distance at any point in the direction it moves. This consistency of linear vectors indicates that the robot moves similar displacement occurs at each point.

In the study, the position and orientation of the robot are calculated precisely angular and linear displacements of the vectorial intersection points presented in Figure 1.
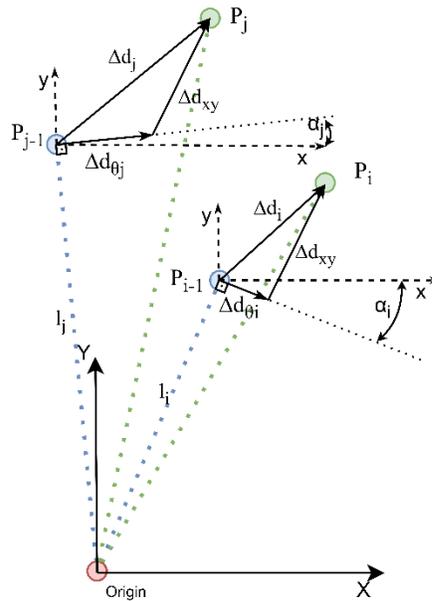
Figure 1. Vectors of intersection points used in position estimation

In the representation in Figure 1, Lidar is located at the origin and the points required for position estimation are distributed from the origin. P_i and P_j points are instantly calculated intersection points. P_{i-1} and P_{j-1} are the previously calculated intersection points. The angular displacement vectors ($\Delta d_{\theta i}$ and $\Delta d_{\theta i}$) are related but different because the distance of the points from the center is different. The relationship between angular displacement vectors is shown in Equation 9. When the vector in Equation 9 is divided into x and y components, Equation 10 is obtained

$$\Delta\theta = \frac{\Delta d_{\theta j}}{l_j} , \Delta\theta = \frac{\Delta d_{\theta i}}{l_i}$$
$$\Delta d_{\theta j} = \frac{\Delta d_{\theta i}}{l_i} l_j \tag{9}$$

$$\Delta d_{\theta jx} = \frac{\Delta d_{\theta i} l_i}{l_j}\cos\alpha_j , \Delta d_{\theta jy} = \frac{\Delta d_{\theta i} l_i}{l_j}\sin\alpha_j \tag{10}$$

Since the locations of the points shown in Figure 1 are known, the vectors Δd_i and Δd_j are calculated. Equations 11 and 12 were obtained by separating these vectors into x and y components.

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$$\Delta d_{ix} = \Delta d_{\theta ix} + \Delta d_x \ , \Delta d_{iy} = \Delta d_{\theta iy} + \Delta d_y \tag{11}$$

$$\Delta d_{jx} = \Delta d_{\theta jx} + \Delta d_x \ , \Delta d_{jy} = \Delta d_{\theta jy} + \Delta d_y \tag{12}$$

The $\Delta d_{\theta jx}$ and $\Delta d_{\theta jy}$ values in Equation 12 were added as explicitly given in Equation 10, and thus, equation 13 was obtained by increasing the parameter similarity in Equations 11 and 12. Equation 14 was obtained by simplifying Δd_x and Δd_y in Equation 11.

$$\Delta d_x = \Delta d_{jx} - \frac{\Delta d_{\theta i} l_i}{l_j} \cos \alpha_j \ , \Delta d_y = \Delta d_{jy} - \frac{\Delta d_{\theta i} l_i}{l_j} \sin \alpha_j \tag{13}$$

$$\Delta d_x = \Delta d_{ix} - \Delta d_{\theta i} \cos \alpha_i \ , \Delta d_y = \Delta d_{iy} - \Delta d_{\theta i} \sin \alpha_i \tag{14}$$

In Equations 13 and 14, two different equations are calculated for Δd_x depending on the i and j values. Equation 15 is obtained by leaving alone the unknown value $\Delta d_{\theta i}$ in these equations. Thus, the magnitude of the angular displacement vector at point i is found. Therefore, when the angular displacement obtained from Equation 15 is substituted in Equation 11, the magnitude of the displacement vector relative to the origin point of the robot is found.

$$\Delta d_{\theta i} = \frac{l_i \left(\Delta d_{jx} - \Delta d_{ix} \right)}{l_j \cos \alpha_j - l_i \cos \alpha_i} \tag{15}$$

2.4. Algorithm of Position Estimation

Within the scope of this study, the data of the lidar sensor is used to determine the position of the robot. As seen in Figure 2, in the first stage, the starting and ending points of the line are determined based on the data received from the lidar sensor. Then, the intersection points of the lines are determined by using the line equations obtained from these points. The differences between these intersection points and the previous points provide important information about the current position and movement of the robot. This method aims to accurately determine the continuous position of the mobile robot through mathematical analysis of lidar data.
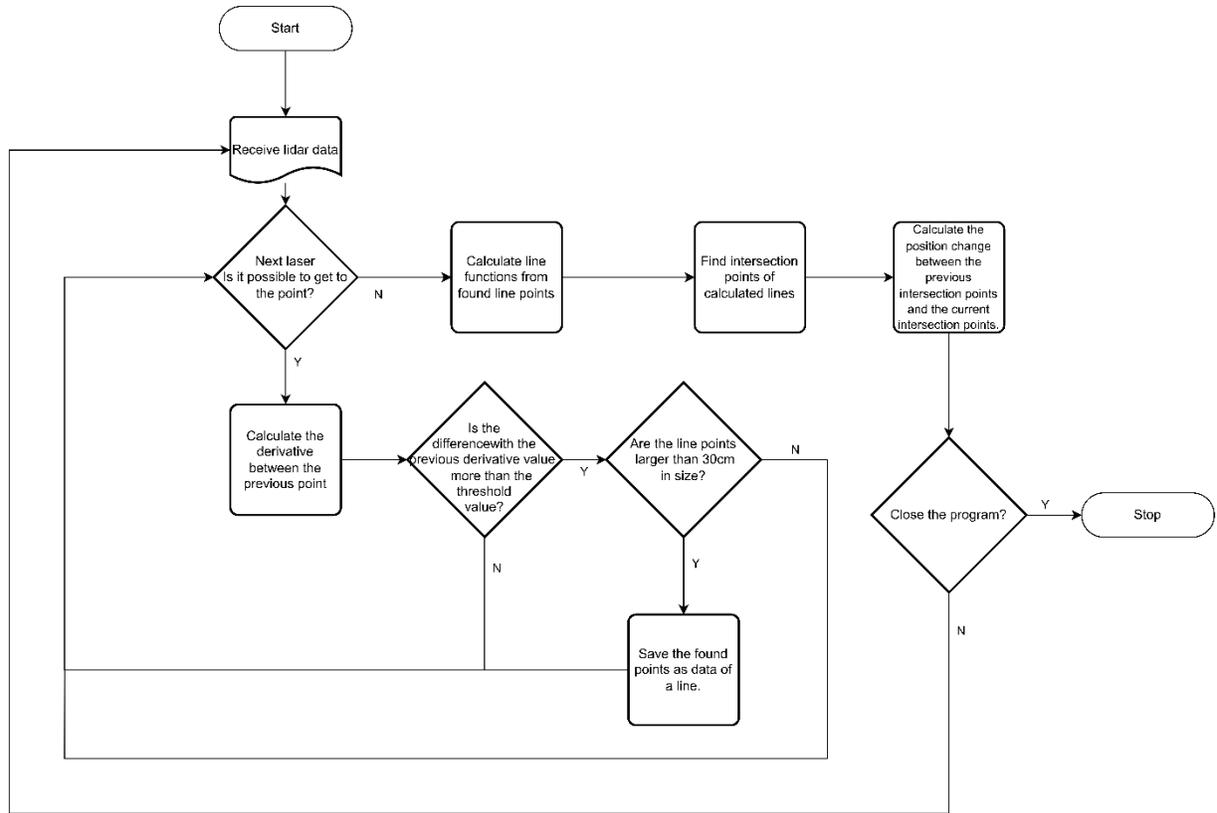
Figure 2. Flow diagram of Lidar-Based Position Estimation Algorithm

The algorithm has been developed in this study was tested in a real environment. The tested mobile robot is the Servant Z250 model shown in Figure 3, produced by Kar Metal.

Figure 3. Servant Z250 Mobile Robot

3. Results

In this study, a lidar-based algorithm was developed, focusing on the localization difficulty of autonomous robots. Thanks to this algorithm, the problem of accurately determining the positions of robots in complex environments has been successfully

solved. In order to explain the stages of the developed algorithm, step-by-step visuals of the lidar-based location detection algorithm are presented in Figure 4.
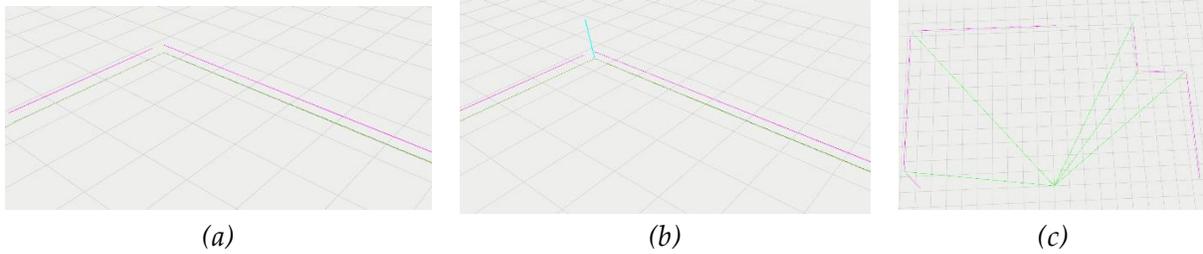
(a)	*(b)*	*(c)*

Figure 4. Working Steps (a: Detection of line b: Intersection points c: Estimation of robot position)

Algorithm testing has been carried out in a phased approach. As shown in Figure 4, lines were first determined from the points. Then, the intersection points of these lines were found and the location calculation was made. The verification process was carried out by comparing the obtained intersection points with the location information in the previous stage.
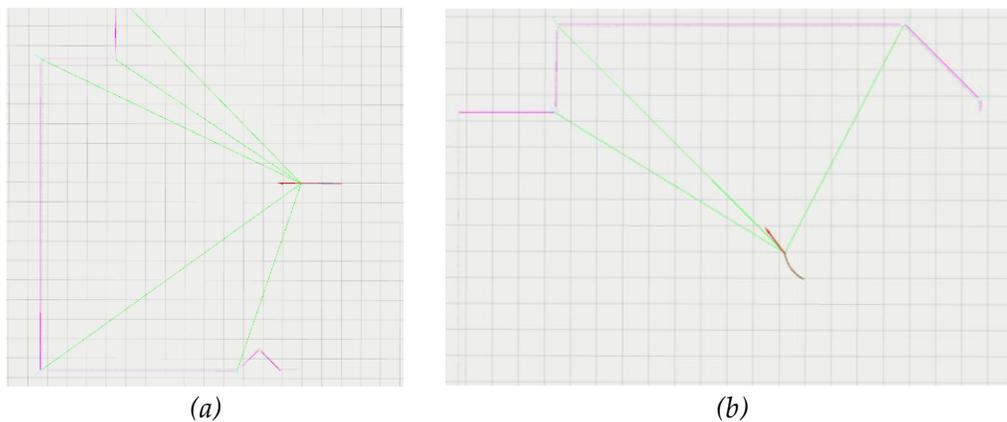
(a)	*(b)*

Figure 5. The motion of robot (a: Linear b: Angular)

As observed in Figure 5, the robot was moved by starting the algorithm. As a result of this movement, the locations the robot passed were drawn in detail using the calculated location information. This drawing visually represents the level of success and accuracy of the algorithm in practice and allows us to understand the path followed by the robot. This observation in the figure reflects the ability of the algorithm to provide successful location detection in real-world applications.

4. Acknowledge

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