Laser Based Localization Techniques for Indoor Mobile Robots

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***Abstract*—The localization problem in indoor environment based on LIDAR measurements is analyzed in this paper. Practical aspects of the localization are discussed including the implementations of the state estimation and registration algorithms. The localization framework developed is sufficient generic to be used in a variety of other autonomous vehicles. The results of the proposed navigation algorithms demonstrate a reliable and accurate position estimation for autonomous vehicles operating in a variety of environments.**

***Keywords*-Mobile robots, localization, laser scan alignment, state estimation.**

I. Introduction

The research addressed in this paper is concerned with the theoretical investigations and practical implementations of reliable localization algorithms for autonomous vehicles in indoor environment based on the laser range scan alignments and state estimation. In the literature, the localization problem is also related to the robot's position estimation in a mapped environment which is also known as the kidnaped robot problem. For localization purposes, the natural landmark-based localization method is one of the most common approaches both indoor and outdoor [1].

Landmark-based navigation vary significantly based on the sensing used to identify landmarks and the types of landmarks to be identified. In the indoor environment features such as walls, corners or heaters can be considered as natural landmarks. For sensing these landmarks we aimed to use for information retrieval a laser range finder, or LIght Detection And Ranging(LIDAR) device together with odometric and IMU sensors mounted on the mobile robot [2].

In the first part of the paper the Extended Kalman filter(EKF) see [3] is presented briefly and the system model used for the vehicle. Further on it is introduced the RANSAC type of algorithms including its implementation details. In the last sections there are highlighted the experimental results together with the conclusions.

II. Extended Kalman Filter as state observer

In real life applications instead of pure linear systems in most cases the systems equations are nonlinear. Some of the successful applications of the Kalman filters have been used for the nonlinear systems, although the principal elements of the estimator remain the same as for the linear case.

A. Process Model for the P3 Skid-Steered Mobile Robot

The kinematic model for the P3 is based on a skid-steered vehicle model is presented by [4]. The motion of the two side wheels of the robot can be controller separately, if the imposed rotation speed at the two side is equal than the robot moves straight forward, else it will turn. This ensures a great flexibility to the robot, even the possibility to turn in the same place. On the other hand, due to the slippage the odometric information is corrupted by systematic errors.

The nominal process model for this type of robot for the discrete time case for the time-instant k is given by:

$$\begin{aligned} x(k+1) &= x(k) + \nabla TV(k)\cos(\varphi(k)) \\ y(k+1) &= y(k) + \nabla TV(k)\sin(\varphi(k)) \\ \varphi(k+1) &= \varphi(k) + \omega(k) \end{aligned} \tag{1}$$

where $\mathbf{u(k)} = [V(k), \omega(k)]$ is the control signal applied to the vehicle containing the linear speed and the rotational speed respectively at time-instant k. The errors due to the control signal V and ω are considered to be additive white noises with Gaussian distributions. The error vector $\delta\mathbf{w}(k) = [\delta V, \delta w(k)]$ is considered to contain both the modeling errors and uncertainty in the control.

B. Observation Model

In case of natural landmarks the predicted range and bearing for each natural landmark j at time-instant k can be computed by:

$$R^j_{nl_k} = \sqrt{[x^j_{nl} - x_{L_k}]^2 + [y^j_{nl} - y_{L_k}]^2} \tag{2}$$

$$\theta = \arctan\left[\frac{y^j_{nl} - y_{L_k}}{x^j_{nl} - x_{L_k}}\right] - \phi_{v_k} \tag{3}$$

where $\left(x^j_{nl}, y^j_{nl}\right)$ id the Cartesian location of the landmark j and (x_L, y_L) is the location of the LIDAR on the vehicle. The landmark observations are corrupted by uncertainties in the range $\mathbf{v}^R_{nl_k}$ and bearing $\mathbf{v}^\theta_{nl_k}$. Finally, the observation model for the landmark observations is:

$$Z^j_{nl_k} = \begin{bmatrix} R^j_{nl_k} \\ \theta^j_{nl_k} \end{bmatrix} + \begin{bmatrix} \mathbf{v}^R_{nl_k} \\ \mathbf{v}^\theta_{nl_k} \end{bmatrix} \tag{4}$$

III. LIDAR Measurements for Registration

A. LIDAR Characteristics and the Measured Environment

The LIDAR measurement returns a bearing and range information about the surrounding reflective surfaces. The functionality of the device that we used is based on the time-of-flight and phase difference of the emitted laser beam reconstructing the distance to the measured object r and the angle θ from which the beam is reflected.

B. RANSAC based registration

The RANSAC(RANdom Sample And Consensus) was first introduced by [5] as a method for parameter estimation for certain models from data affected by noise and corrupted by outliers.

As we were interested in the localization of the LIDAR rather than the mapping problem, a rigid approach on the data searching was adopted. Starting from this idea, the RANSAC can be seen as an optimization algorithm for the cost function. In [6] the original algorithm is redefined by considering the estimator as part of the M-estimator family, being known as MSAC.

As a comparison for the original RANSAC and MSAC $N = 500$ points were considered with half of them being inliers. During the tests, the σ variance was gradually increased. The cost function was more relevant for the algorithm comparison. A summary of a typical run is presented in the Table I. As it can be seen in this table the MSAC algorithm proves better performance than the classical RANSAC, hence this was used further on.

Table I
RANSAC and MSAC comparison

σ(mm)	J_{RANSAC}	J_{MSAC}
20	34000	32000
40	120000	118000
60	250000	232000
80	inf	389000

For the scan registration problem between two consecutive robot movements the displacement can be formulated as $\hat{m} = (m_x, m_y, m_\theta)$. The estimated transformation $\hat{m}$ can be used for the position estimation of the robot.

IV. Experimental Results

We carried out the experiments on the corridors of the TUC-N, with a P3 type mobile robot on which it was mounted the LMS200 SICK laser range finder. For the IMU and odometric measurements the presented EKF algorithm was used to estimate the positions.

Further more for these rather poor estimates the displacement information extracted from the range alignment was used to correct the position of the robot. For a typical scan alignment, the part on which the two scans overlap are more than 50%, and in such cases even the presence of dynamic objects (e.g. human leg forms) is tolerated by the registration algorithm as it can be seen on Fig. 1.

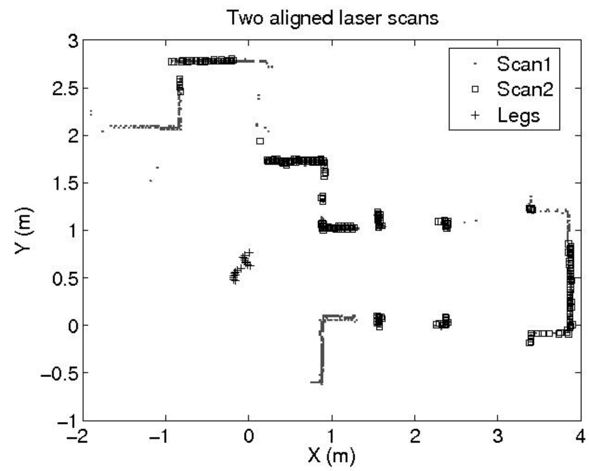

Figure 1. Two consecutive aligned laser scans

Even though the measurements with the laser range finder are quite accurate in the scale in which the movements of the vehicle were done, sometime the registration algorithm fails to give coherent information. For this is essential to combine the with the data from the dead-reckoning systems.

V. Conclusions

The main idea of this work was to apply for real life experiments the well known RANSAC and EKF algorithms. Also some extensions of the RANSAC algorithm were discussed. The generality of the presented approach was ensured by not taking specific constrains in the navigation problem like artificial landmarks.

References

[1] R. Madhavan, H. Durrant-Whyte, and G. Dissanayake, "Natural landmark-based autonomous navigation using curvature scale space," *Proceedings of the IEEE International Conference on Robotics and Automation*, 2002.

[2] D. Cole and P. Newman, "Using laser range data for 3d slam in outdoor environments," 2006, pp. 1556–1563.

[3] Y. Bar-Shalom, X. Li, and T. Kirubarajan, *Estimation with Applications to Tracking and Navigation: Theory, Algorithms, and Software*. New York,: Wiley, 2001.

[4] K. Kyriakopoulos and G. Anousaki, "A dead-reckoning scheme for skid-steered vehicles in outdoor environments," *Proc. Int. Conf. Automation*, pp. 580–585, May 2004.

[5] M. Fischler and R. Bolles, "Random sampling consensus: a paradigm for model fitting with application to image analysis and automated cartography," vol. 24, 1981, pp. 381–395.

[6] P. Torr and A. Zisserman, "Mlesac: A new robust estimator with application to estimating image geometry," *Computer Vision and Image Understanding*, vol. 78, pp. 138–156, 2000.