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Laser Based Pose Tracking

Patric Jensfelt

Signal, Sensors & Systems
Royal Institute of Technology
SE-100 44 Stockholm

Henrik I. Christensen

Autonomous Systems
Royal Institute of Technology
SE-100 44 Stockholm

Abstract

The trend in localization is towards using more and more detailed models of the world. Our aim has been to answer the question "How simple a model can be used to provide and maintain pose information in an in-door setting?". In this paper a Kalman filter based method for continuous position updating using a laser scanner is presented. By updating the position at a high frequency the matching problem becomes tractable and outliers can effectively be filtered out by means of validation gates. Presented experimental results show that the method performs very well in an in-door environment.

1 Introduction

A notorious problem in mobile robotics is localization and maintenance of a position estimate. Traditionally position feedback is provided by odometry, but due to slippage etc., a drift that is proportional to the maneuvers is introduced. To circumvent this problem it is necessary to complement the odometry based estimation with input from other sensory modalities. Most mobile systems use ultra-sonic sonars for localization. An excellent overview of such systems can be found in [1]. The spatial resolution of sonars is limited, which requires significant post-processing of data to provide accurate position updating. An alternative to sonars is laser based position estimation. Traditionally laser scanners have been quite expensive and they have thus primarily been used in hostile or space applications, where cost is of secondary importance. Recently a new generation of laser scanners has been introduced into the market, which allow for use of such scanners even for regular applications. Some of the advantages of laser scanners are that they have the potential to deliver data at a high rate (over 25Hz) and that their spatial resolution typically is as good as 1mm to 1cm at an angular resolution of 0.5°.

With laser based scanners it is possible to provide very detailed models of the environment and utilize these for localization and pose tracking. One problem with the detailed models is that the computational complexity often limits the achievable updating frequency. In general the trend has been towards use of more and more detailed models. In this paper the opposite problem is addressed. The question raised here is "How simple a model can be used to provide and maintain pose information in an in-door setting?".

In the discussion of models two different approaches have been explored in the literature: i) grid-based [2, 3] and ii) feature-based [4, 5]. The grid-based approach is attractive as the semantic interpretation is very limited and it is straight forward to perform online updating. Unfortunately the model complexity can be very large, especially for large scale in-door environments, like our laboratory (10 by 70 meters). In the feature based approach laser scans are segmented into a set of features, e.g., line segments, corners, inflection points, etc. The features from the sensor is then matched to the model. The matching is potentially NP-hard, which can result in prohibitive processing requirements, when using detailed world models. In this paper we will use a feature based approach and investigate the use of "simple" world models to allow for fast updating.

Initially a model of the uncertainty for the sensor is developed, as a basis for uncertainty weighted fusion of readings. The problems of absolute localization and pose tracking are then introduced. From this discussion a least square estimator for pose tracking is developed using a Kalman filter approach. A key problem addressed is the filtering of data to provide a robust basis for matching. To simplify matching over time and suppress outliers, validation gates are computed and used for initial filtering of data. The developed technique is tested in an in-door environment where a significant amount of clutter is present.

The experiments involve evaluation in multiple rooms, to demonstrate operation in varying settings. The experiments also involve pose tracking while passing between rooms. Finally the results are summarized and avenues for future research are outlined.

2 Characteristics of the Sensor

In this work a proximity laser scanner, the PLS 200 from SICK Electro-Optics, is used. The SICK sensor can scan the environment at a rate of 25Hz. Due to hardware limitations (max serial speed 38.4 kBaud) we get a maximum sampling rate of 3Hz. The sensor is placed approximately 93 cm above ground on a Nomad200 platform as shown in Figure 1.

Figure 1: The Sick sensor is placed on top of a Nomad200 platform equipped with an array of sensors.

The SICK scanner uses a Time of Flight (TOF) ranging principle that is driven by a 6 GHz clock, which provides a ranging resolution of 50 mm. The laser scanning is performed using a rotating mirror that rotates at 25Hz. In practice the sensor provides a polar range map of the form (α, r), where α is the angle from 0° - 180° discretized into 0.5° bins. Analyzing the output from the sensor it is apparent that the uncertainty of the data is uniformly distributed over the ranges $[-25, 25]$ mm and $[-0.25°, 0.25°]$, respective. Converting the polar data into a Cartesian frame of reference we obtain:

$$\vec{c} = \begin{bmatrix} a \\ b \end{bmatrix} = r \begin{bmatrix} \cos\alpha \\ \sin\alpha \end{bmatrix}. \tag{1}$$

Let Δr and $\Delta\alpha$ define the size of the area over which the parameters r and α are distributed. The density functions can be written as $f_r(r) = \frac{1}{2\Delta r}$ for $r \in [\bar{r} - \Delta r, \bar{r} + \Delta r]$ and $f_\alpha(\alpha) = \frac{1}{2\Delta\alpha}$ for $\alpha \in [\bar{\alpha} - \Delta\alpha, \bar{\alpha} + \Delta\alpha]$. The variance in the a and $b$directions, respectively, can be derived from straight forward calculations assuming that the uncertainty in r and α is independent. The result being:

$$\begin{aligned}
\sigma_{aa} = \;& \tfrac{1}{2}(\bar{r}^2 + \tfrac{1}{3}\Delta r^2)\left(1 + \cos(2\bar{\alpha})\cos(\Delta\alpha)\tfrac{\sin(\Delta\alpha)}{\Delta\alpha}\right) \\
& -\bar{r}^2\cos^2(\bar{\alpha})\left(\tfrac{\sin(\Delta\alpha)}{\Delta\alpha}\right)^2 \qquad (2) \\
\sigma_{bb} = \;& \tfrac{1}{2}(\bar{r}^2 + \tfrac{1}{3}\Delta r^2)\left(1 - \cos(2\bar{\alpha})\cos(\Delta\alpha)\tfrac{\sin(\Delta\alpha)}{\Delta\alpha}\right) \\
& -\bar{r}^2\sin^2(\bar{\alpha})\left(\tfrac{\sin(\Delta\alpha)}{\Delta\alpha}\right)^2 \qquad (3) \\
\sigma_{ab} = \;& \tfrac{1}{4}(\bar{r}^2 + \tfrac{1}{3}\Delta r^2)\cos(2\bar{\alpha})\cos(\bar{\alpha})\tfrac{\sin(\Delta\alpha)}{\Delta\alpha} \\
& -\bar{r}^2\sin(\bar{\alpha})\cos(\bar{\alpha})\left(\tfrac{\sin(\Delta\alpha)}{\Delta\alpha}\right)^2 \qquad (4)
\end{aligned}$$

In our experiments we settled for using a, from a mathematical point of view, much simpler model of the uncertainty. We assumed the uncertainty to have an independent Gaussian distribution in a and b direction with a standard deviation of 50 mm. This a very crude model, but one that has proven to be adequate in our experiments.

3 Localization

Localization is an essential component in most systems. It has been studied extensively in the literature, using a variety of different sensors. As already mentioned in the introduction the most common sensor is simple odometry using for example quadrature encoders. The odometry is, however, subject to drift etc.

3.1 Previous Work

The ultrasonic sensor has been, is and will probably remain the most widely used complement to odometry for mobile robot localization. Many techniques has been developed, both grid-based techniques (e.g. Moravec and Elfes [3] and Borenstein & Koren [6]) and feature based techniques (e.g. Crowley [4] and Leonard & Durrant-Whyte [5]).

3.2 Absolute Localization vs Pose Tracking

Localization is here interpreted as re-initialization of the position estimate and a process that is carried out at a set of discrete instances, for example upon entering a room. Given the large uncertainty that is associated with localization, i.e. the position estimate might be off by meters, the process is often slow. This is, however, often of secondary importance as the process only is carried out at discrete instances. Given availability of frequent (and reliable) sensory information it is possible to change the localization process into a continuous tracking task in which landmarks in the environment are tracked over time and used for maintenance of the position and orientation (together termed the pose) estimate. Localization is then used for boot-strapping of the tracking and given limited motion between pose updates, the matching process is suddenly a tractable problem.

In an in-door environment the physical boundary (the walls) of a room can often be approximated as a rectangle. An interesting research issues is then, "is it possible to perform localization and pose tracking using a simple rectangular model of a room?".

4 Position Tracking

4.1 Idea

The idea behind the pose tracking method presented here is simple. By using the information extracted from detecting walls, a good estimate of the pose can be generated. Let $\mathbf{x}_k = \begin{pmatrix} x & y & \theta \end{pmatrix}_k^T$ represent the pose of the robot at time k. In the state space formulation of the system that follows, this is the state vector. By modeling the odometry as a deterministic input (with some noise) we get:

$$\mathbf{x}_{k+1} = \mathbf{x}_k + \mathbf{g}_k + \mathbf{w}_k \tag{5}$$

where $\mathbf{g_k}$ is the input from the odometry and $\mathbf{w_k}$ represents the process noise. $\mathbf{w_k}$ is a measure of the odometric quality of the system. The characteristics of the odometry has been studied through a series of tests (see Appendix). The odometric noise is modeled as dependent on two factors, the distance traveled and the amount of steering. The uncertainty in distance traveled is 1%, and each meter traveled adds 0.6° in standard deviation to the orientation estimate. Steering the wheels increases the standard deviation in orientation by 0.1% of the amount of steering. Borenstein [7] points out one danger with having a statistical model for the odometry "they cannot anticipate the unpredictable and potentially "catastrophic" effect of larger bumps or objects encountered on the floor". This is a point well worth considering and it will have to be taken into consideration in the future.

The measurement equation can be described by

$$\mathbf{z}_{i,k} = \mathbf{h}_i(\mathbf{x}_k) + \mathbf{v}_{i,k}, \; i = 1, \ldots, N \tag{6}$$

where $\mathbf{h_i}$ represents a possibly non-linear measurement function and $\mathbf{v_{k,i}}$ is the corresponding measurement noise. In our case the measurement update is performed in multiple steps, one for each wall, where each wall will give information about the position in either x or y direction plus the orientation. The transformation from the pose of the robot to the measurements from the wall is a non-linear function, but we have chosen to model all nonlinearities as part of the noise. This is possible as we have chosen the walls parallel to the coordinate axes and therefore a distance to a wall corresponds to a position in x or y direction, respectively (see Figure 2).

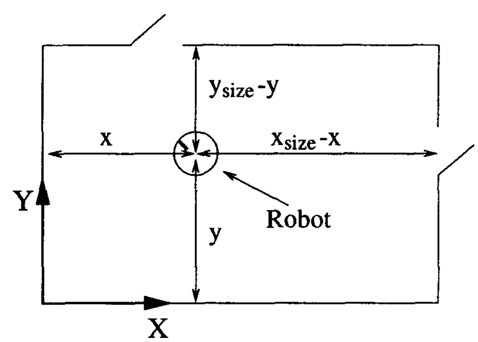

Figure 2: Each wall in a rectangular room will give information about either the x or y position in the room.

$$\mathbf{z}_{i,k} = \begin{pmatrix} x \text{ or } y \\ \theta \end{pmatrix}_{k,i} + \begin{pmatrix} \sigma_x \text{ or } \sigma_y \\ \sigma_\theta \end{pmatrix}_{k,i}, \; i = 1, \ldots, N \tag{7}$$

Let $\hat{\mathbf{x}}_{k|k}$ be the estimate of the pose at time k given past measurements up until time k. The prediction stage of the tracking is then:

$$\hat{\mathbf{x}}_{k+1|k} = \hat{\mathbf{x}}_{k|k} + \mathbf{g}_k. \tag{8}$$

The measurements are used in sequence to update the pose.

$$\begin{aligned} \hat{\mathbf{x}}_{k+1|k,i} &= \hat{\mathbf{x}}_{k+1|k,i-1} \\ &+ \mathbf{K}_{i,k} \left(\mathbf{z}_{i,k+1} - C\hat{\mathbf{x}}_{k+1|k,i-1} \right) \end{aligned} \tag{9}$$

where $\hat{\mathbf{x}}_{k+1|k,0} = \hat{\mathbf{x}}_{k+1|k}$, $\hat{\mathbf{x}}_{k+1|k,N} = \hat{\mathbf{x}}_{k+1|k+1}$, $\mathbf{K}_{i,k}$ is the Kalman gain and C is either $\begin{pmatrix} 1 & 0 & 0 \\ 0 & 0 & 1 \end{pmatrix}$ or $\begin{pmatrix} 0 & 1 & 0 \\ 0 & 0 & 1 \end{pmatrix}$ depending on if x or y is measured.

4.2 Filtering of Data

The filtering of data is performed as follows (see dashed rectangle in Figure 3).

1. Data is run through four validation gates, one for each wall. This could be extended to be n walls, as well as other features.
2. A local Range Weighted Hough Transform[1] [8] is performed on each set of validated data.
3. A second stage validation is carried out. The validation uses position and orientation estimates that have been updated using the RWHT.
4. Finally Least Squares fits are made using the points that are close to each wall, corresponding to peaks in the RWHT.

Based on the filtering a set of zero to four wall hypotheses are available for parameter updating (using a rectangular room model). Each wall will have an uncertainty attached, which depends on the data that was used to hypothesize the location of the wall. We have used the model from [9] for the least square algorithm, which also provides estimates of the uncertainty for the line parameters. The representation of the walls is (ρ, φ) where $\rho \in [0, \infty)$ and $\varphi \in [0, 360°)$. ρ is a measure of the distance to one of the walls, i.e. it will give either the x or y position in the room. φ is a measure of the orientation of the robot.

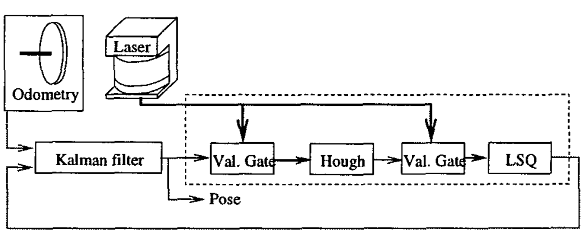

Figure 3: Signal flow in the localization module.

[1] Like a standard Hough transform except that the vote of a point far away carries more weight than a point close to the sensor. The idea is that points close to the sensor tend to be closer together and therefore they will influence more unless a range weight is introduced.

4.2.1 The Validation Gates

Given an initial estimate of the pose of the robot, it is possible to predict where the wall(s) will be in the data. The uncertainty in the pose as well as the quality of the data will determine the size of the validation gates. The locations of the validation gates are based on the prediction of the pose of the robot and the map of the current room. The size of each validation gate is defined by two parameters (see Figure 4), the size of the initial opening, δ and the opening angle, γ.

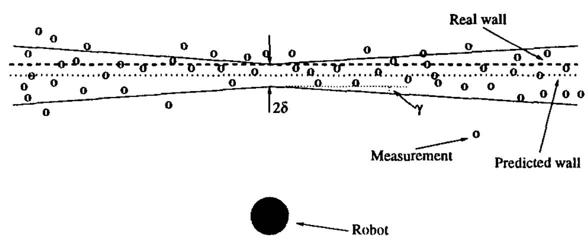

Figure 4: Validation gate where the error in the prediction of the wall and the size of the validation gate were scaled for illustration purposes.

4.3 Managing the Size of the State Uncertainty

In a Kalman filter the so called innovation process, or the difference between what is predicted and what is actually measured, ensures convergence towards the true states. The amount of effect the innovation will have on the state estimate depends on the uncertainty both in the state estimate and the measurement. The lower the noise level is on the state estimate the less effect the innovation will have. This will cause a problem in the case of a mobile robot tracking its position since we want the measurements to compensate for wheel slippage etc. One way of handling this is simply to set a lowest allowed level for the uncertainty in the state estimate. This has proven most effective in our experiments.

In passing from one room to another the risk for unmodeled errors to occur is larger than otherwise as the robot might slip on the threshold and/or bump into things. In our experiment the uncertainties are increased with 100 mm in both x and y direction and the angular uncertainty is increased by 2° (the values refer to an increase in the standard deviation).

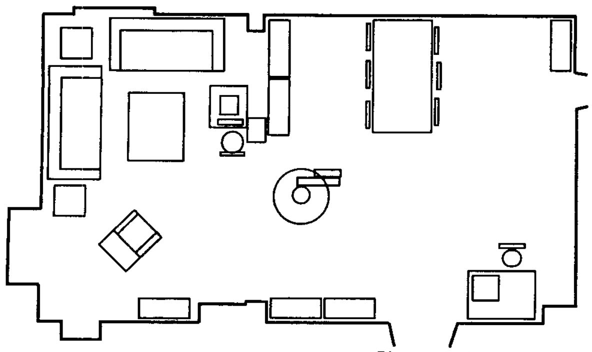

Figure 5: Sketch of the living-room seen from above.

5 Experimental Results

In this section we will show that the presented method can handle rooms that are far from being sparsely furnished.

5.1 General Description of Experiments

The experiments have been performed on the Nomad200 platform shown in Figure 1. The localization module is a part of a larger system that already has capabilities to do obstacle avoidance, pass through doors and go between points, etc. No active sensing strategy has been used. The platform is equipped with a lift mechanism that makes it possible to pick up simple objects. The obstacle avoidance behavior in the system makes sure that the lift as well as the the platform itself do not hit anything. This means that even though no active sensing strategy has been implemented the direction of the sensor will change as a result of the obstacle avoidance.

5.2 Different rooms

At a first glance it might appear as though the method presented will fail as soon as there are no clear wall to be seen by the sensor. To prove that this is not the case we performed experiments in many different rooms in our laboratory. Here we will present the results from three different rooms.

Living-room Our mobile robot lab is setup as a living-room with IKEA furniture. The room is approximately 8.6 by 5 m. A top view of the room can be found in Figure 5 and two pictures of the same room from different view points are shown in Figure

Figure 6: View of the south-east and north-west corners of the living room.

6. As can be seen from the figures above the living room is quite cluttered. The only wall that provides a clear view is the wall on the right in Figure 5. Many experiments were performed in the living-room and only once did the robot make a significant error in the estimation of the pose. This occurred after having moved for minutes without having had any input from neither the top or the lower wall (refers to Figure 5). As the robot moved the uncertainty in that direction grew. As the uncertainty increased the size of the validation gates increased and more data were left unfiltered. Eventually the validation gates were open enough to let data that came from the bookshelves and the pillar on the lower wall form a hypothesis strong enough to be interpreted as the wall. When this occurred the estimate in the position was offset by approximately 300 mm, corresponding to the depth of the bookshelves. To tackle this situation the uncertainty in all directions were increased manually by 400 mm (standard deviation) and the robot was given a clear view of three of the walls (lower, left and top walls) which resulted in the robot returning to the correct pose again.

Office This is a typical office in our laboratory. The room is so small that the allowable movements of the robot are very limited. The rectangular model of this office room is approximately 5 by 3 meters. The office is divided by a cubicle divider into two parts. This room posed no problem either, partly because the limited movements in the room ensured this, even though two orthogonal wall were not seen all the time, the uncertainty never grew very much.

Corridor The corridor at the ground floor of our laboratory is approximately 55 m long and the width is about 2.3 m (see Figure 8). The corridor has been modeled as a single room in our experiments. It is obvious that the problem in the corridor is going to be maintenance of a good estimate of the position in the length direction of the corridor. Since the corri-

Figure 7: Office

Figure 8: Corridor

dor is modeled as a rectangle, the only two possible sources of information about the position along the corridor comes from the two short walls. When moving far away (>≈ 15 m) from the short walls they can no longer be used, as too few points are accumulated. This implies that almost half the length of the corridor has to be driven using only odometric information for position updating along the corridor. The biggest problem with the odometry is usually that rotational errors result in big translational error, especially over long distances. This is true for our platform too. In the corridor this could potentially lead to very big errors, but the fact that the orientation of the platform is estimated with high accuracy compensates for the rotation of the platform. The biggest error left is the error that comes from mapping the number of wheel rotations to distance traveled.

Many experiments were performed and in most cases (> 75%) the robot were able to drive from one end of the corridor to the other while maintaining an accurate estimate of its pose. When coming close enough (<≈ 15 m) to the other end, the short wall would be tracked and the uncertainty would go down.

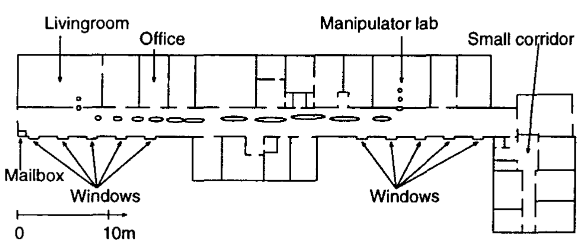

Figure 9: Result of moving from the living-room to the manipulator lab. The size of the uncertainty ellipses are made bigger to be seen easier.

5.3 Navigation Between Rooms

The experimental results in the previous section demonstrated that the pose tracking method worked very well in different types of rooms. ¿From the experiment in the corridor it is evident that the estimate of the position along the corridor might cause problems when moving in the mid area of the corridor. One way to solve this problem would be to extend the model and track the position of doors as well. As we are investigating the limit of using a "simple" model alternatives are more interesting. In Figures 9 and 10 the result of driving from the living room, through the corridor and into the manipulator laboratory is shown. It can be seen how the uncertainty grows large in the mid area where no input in the direction along the corridor is given. As the robot approaches the manipulator laboratory the short wall at that end of the corridor becomes strong enough and the uncertainty decreases. Two approaches for keeping the uncertainty can easily be identified i) use active sensing to maximize the use of the short walls and ii) go into a room on its way to update the position in the direction of the corridor.

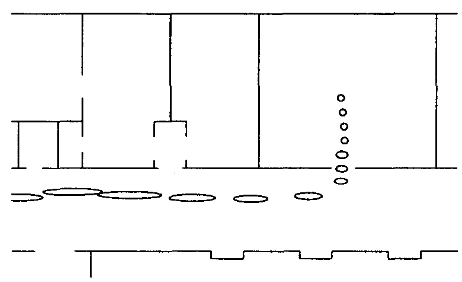

Figure 10: A close up of the situation when passing from the corridor to the manipulator lab.

6 Conclusions

It this paper we have shown that it is possible to continuously track the pose of a robot, modeling each room as a "simple" rectangle. The answer to the question posed at the beginning of the paper must thus be that the model can be this simple in a typical in-door office setting. It has been shown by experiments that the method can handle a variety of room types and that moving between rooms poses no problem either. On the contrary, when moving from one room to another, the position of the robot could potentially be updated very accurately as the door has a well defined position in the world. Having structures that form a line that are close to and parallel with a real wall can result in errors in the data association as was seen in the experiments in the living-room.

An active sensing strategy is still missing. Such a strategy might significantly improve the performance as in many situations the robot could have gotten much better information by looking in another direction. The living-room is a perfect example of this.

Future research will also address the questions: i) Allowable clutter before the tracking fails? ii) How non-rectangular must a room be before the method fails? I.e. does it fail if applied in an old building with non-orthogonal walls?

7 Acknowledgement

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Appendix

A series of tests were performed in order to characterize the odometric noise. One of the test was the UMBmark [1]. This test was designed for a differential drive platform, but it still gives clues to the performance of the odometry on our synchrodrive Nomad200 platform. In theory the platform base should have the same direction at all time, but moving the platform changes the direction of the base. We decided to use the distance traveled and the amount of steering to parameterize the odometry model.

When driving the robot in our long corridor it was found that the scaling was wrong. In order to get a zero mean estimate of the distance traveled, the value given by the odometry has to be scaled by a factor 1.006. This is part of the odometric model. The standard deviation was about 1% of the distance traveled.

Another test that was performed was to look at how the steering effects the orientation of the platform. By placing the robot in front of a wall with a laser pointer at the wall, the change in angle can be measured when the wheels move. The tests indicated a bias of 0.1% of the amount of steering with a standard deviation of about the same magnitude.

Translating the robot without steering will still effect the orientation of the platform. For each meter traveled the platform will rotate about 0.6%. The problem here is that it is not perfectly predictable, i.e. a change in orientation is not always be observed. This was modeled as a bias of 0.6% with a standard deviation of the same magnitude.

Further tests have to be conducted to get a more truthful model of the odometry. It is good to have an accurate model as long as nothing unforeseen happens. When something unforeseen occurs trusting in the odometric model might prove fatal. It is therefore of great importance to be able to detect situations where the odometry fails.