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Simulation of nonlinear filter based localization for indoor mobile robot

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Abstract: Robot localization is a position estimation issue. Gaussian or non parametric executions ought to be considered to estimate position of robot. In this paper we use nonlinear filter approach to tackle the robot position estimation issue. The aim of this paper is to acquaint with the kalman filter and the extended kalman filter algorithm for determining the position of a mobile robot. The performance of EKF and the quality of position estimation depends on the exact a priori information of process and measurement noise covariance matrices. Taking this problem into a account and to solve mistakes show in estimations the simulation results can be drawn with better accuracy of the filters in estimating the robot's localization.

Keywords: Localization; Extended kalman filter; Mobile robot, Estimation.

1. INTRODUCTION

The fundamental problem in mobile robotics is localization. In this paper we introduce extended kalman filter algorithm to solve the localization problem [2],[3],[5][1]. However, localizing a mobile robot using only odometry is inaccurate, since the error arising from the uncertainties of the odometric model and the measurement noise of the odometric sensor is accumulating [1] [6]. A robot can simultaneously build a global environment map and then use this map to localize itself in the environment, which is known as a SLAM [7] (simultaneous localization and mapping) algorithm. In the literature, many approaches and algorithms involved in solving the SLAM, localization and mapping problem have been proposed. Filtering is a very used method in engineering and embedded systems. A good filtering algorithm can reduce the noise from signals while retaining the useful information [1].

This paper is organized as follows. In Section 2 the prediction step and the correction step of the KF are described. Section 3 EKF equations are described. In Section 4 are the simulation results of EKF localizing the robot in an indoor environment In Section 5paper is concluded.

2.KALMAN FILTER

Within the significant toolbox of mathematical tools that can be used for stochastic estimation from noisy sensor measurements, one of the most well-known and often-used tools is what is known as the *Kalman filter*. It is ***recursive*** so that new From a theoretical standpoint, the Kalman filter is an algorithm permitting exact inference in a linear dynamical system, which is a Bayesian model similar the state space of the latent variables is continuous and where all latent and observed variables have a Gaussian distribution. Equations of Kalman filter

Model

$$g_k = U_k g_{k-1} + A_k n_k + W_k$$

where

- U_k is the state transition model which is applied to the previous state g_{k-1}
- A_k is the control-input model which is applied to the control vector n_k;
- w_k is the process noise with covariance Q_k

$$D_k = E_k g_k + m_k$$

D_k is at time k an observation

Predict

$$\hat{g}_{k|k-1} = U_{k\hat{g}_{k-1|k-1}} + A_{kn_k}$$

$$C_{k|k-1} = U_k C_{k-1|k-1} U_k^T + Q_K$$

Update

$$\tilde{y}_{k=D_k - E_K \hat{g}_{k|k-1}}$$

$$S_k = E_k C_{k|k-1} E_k^T + J_k$$

$$K_k = C_{k|k-1} E_k^T S_k^{-1}$$

$$\hat{g}_{k|k} = \hat{g}_{k|k-1} + K_k \hat{y}_k$$

$$C_{k|k} = (I - K_k E_k) C_{k|k-1}$$

Extensions of Kalman Filter
- Validation gates - rejecting outlier measurements
- Serialization of independent measurement processing
- Numerical rounding issues -avoiding asymmetric covariance matrices
- Non-linear Problems - linearising for the Kalman filter

3.THE EXTENDED KALMAN FILTER (EKF)

As described above the Kalman filter addresses the general problem of trying to estimate the state of a discrete-time controlled process that is governed by a *linear* stochastic difference equation. But what happens if the process to be estimated and (or) the measurement relationship to the process is non-linear? Some of the most interesting and successful applications of Kalman filtering have been such situations. A Kalman filter that linearizes about the current mean and covariance is referred to as an *extended Kalman filter* or EKF. The Extended Kalman filter (EKF) is one of the nonlinear filter which has become a standard technique used in a number of nonlinear estimation and machine learning applications. Equations of extended kalman filter.

Model

$$g_k = f(g_{k-1}, n_k) + w_k$$

$$D_k = h(g_k) + m_k$$

w_k and m_k are the process and observation noises with covariance $\mathbf{Q}_k$ and J_k. n_k is the control vector.

Predict

$$\hat{g}_{k|k-1} = f(\hat{g}_{k-1|k-1}, n_k)$$

State estimate predicted

$$C_{k|k-1} = U_k C_{k-1|k-1} U_k^T + Q_k$$

Covariance estimate predicted

Update

$$\boldsymbol{\hat{y}_k = g_k - h(\hat{g}_{k|k-1})}$$

$$\boldsymbol{S_k = E_k C_{k|k-1} E_k^T + J_k}$$

Kalman gain $\boldsymbol{K_k = C_{k|K-1} E_k^T S_k^{-1}}$

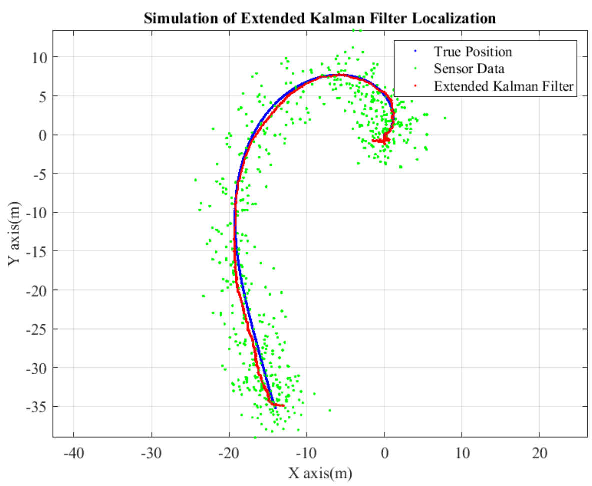
$$\hat{g}_{k|k} = \hat{g}_{k|k-1} + K_k \tilde{y}_k$$

State estimate updated

$$C_{k|k} = (I - K_K E_K) C_{k|k-1}$$

Covariance estimate updated

4. SIMULATION RESULTS



5. CONCLUSION

Keeping in mind the end goal to utilize mobile robot for any application, robot should have a precise data. The greater part of the restriction frameworks depend on the sensors or the guide of the earth. In this way, restriction is a noteworthy prerequisite for a mobile robot. The exploring operation in mobile robot more often than not utilizes the odometry sensors to find its position. These odometry sensors figuring the quantity of upsets that the wheels make while driving and turning. This perusing of the wheel is accustomed to assessing the uprooting over the ground to give a make of the area of the robot. Along these lines of limitation have numerous issues, for example, wheel slippage, surface unpleasantness, and mechanical resistances. This research work, proposes a robot limitation framework taking into account the extended kalman filter to beat the issues of restriction in mobile robot. The exploratory consequence of this paper delineates the strong and the precision of the proposed framework. MATLAB simulation of mobile robot is performed using Extended Kalman Filter.

REFERENCES

[1] Teslic, L., Krjanc, I. & Klanar, G. (2011), ‘EKF-based localization of a wheeled mobile robot in structured environments’, Journal of Intelligent and Robotic Systems 62 (2),187-203.

[2] Caius Suliman1, Cristina Cruceru1, Florin Moldoveanu1,'Mobile Robot Position Estimation Using the Kalman Filter', Scientific Bulletin of the Petru Maior University of Tirgu Mures Vol. 6 (XXIII), 2009 ISSN 1841-9267.

[3] liver Bittel, Michael Blaich, “Mobile Robot Localization Using Beacons and the Kalman Filter Technique for the Eurobot”, Competition',Research and Education in Robotics - EUROBOT 2011

[4] d Ramazan Havangi, Mohammad Ali Nekoui and Mohammad Teshnehlab, “Adaptive Neuro-Fuzzy ExtendedKalman Filtering for Robot Localization” IJCSI International Journal of Computer Science Issues, Vol. 7, Issue 2, No 2, March 2010

[5] Hamzah Ahmada & Toru Namerikawab, “Extended Kalman filter-based mobile robot localization with intermittent measurements”, Systems Science & Control Engineering: An Open Access Journal Volume 1, Issue 1, 2013.

[6] L. Cheng, Y.J. Wang, "Localization of the autonomous mobile robot based on sensor fusion," Proceedings of IEEE International Symposium on Intelligent Control, pp. 822-826, 2003.

[7] H. Durrant-Whyte and T. Bailey, "Simultaneous localization and mapping: Part I," IEEE Robotics and Automation Magazine, vol. 13 (2), pp. 99-108, 2006