Simulation of Localization for Indoor Mobile Robot using Extended Kalman Filter

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Abstract - *Simultaneous localization and mapping (SLAM) is a key component in self-driving vehicles and other autonomous robots enabling awareness of where they are and the best routes to where they are going. By creating its own maps, SLAM enables quicker, more autonomous and adaptable response than pre-programmed routes. The main major problems with SLAM are localization errors accumulate which causes substantial deviation from actual values and in some cases localization fails. In this paper, a novel methodology is proposed to solve the SLAM problem of mobile robot with extended Kalman filter (EKF) algorithm. The robot used for this purpose is a differential drive robot which uses various types of cameras and sensors such as Kinect sensor, ultrasonic sensor and other technologies to understand its environment so that it can more effectively map, navigate, avoid obstacles and adjust to changes. The accuracy of these measurements and the performance of the corresponding SLAM algorithm directly affect the overall success of the system. The results of simulation indicate that EKF SLAM algorithm can localize the robot and landmarks precisely and the error of landmark's estimation confluences better than general SLAM.*

Key Words: Localization, differential drive robot, extended Kalman filter, prediction, correction.

1. INTRODUCTION

Robot localization is the fundamental task in mobile robotics. In some cases localization fails and the position of differential drive robot on the map is lost. The localization problem then becomes one of the estimating the robot position and orientation within the map using information gathered from sensors [1]. In this paper we introduce the extended Kalman filter algorithm to solve the localization problem [1][2][3][4]. Robot localization techniques need to be able to deal with noisy observations and generate not only an estimate of the robot location but also a measure of the uncertainty of the location estimate. SLAM algorithm is a method used for autonomous vehicles that can build map and localize vehicle in that map at the same time [1][5]. SLAM algorithm allows the vehicle to map out unknown environment. In the literature, many methods, approaches and algorithms involved in the solving localization and mapping problem has been proposed. An extended Kalman filter is good filtering algorithm which involves landmark detection, data association, and several steps in localization, obtaining covariance matrices for the relation between variables and finally Bayesian update to reduce noise and effectively localize and map the environment.

This paper is organized as follows. In Section II extended Kalman filter equations are described. In Section III the simulation results of EKF localizing the robot in an indoor environment is described. In Section IV paper is concluded.

2. EXTENDED KALMAN FILTER ALGORITHM FOR LOCALIZATION

Kalman filtering (KF) is an algorithm that provides estimates of some unknown variables given the measurements observed over time. It is a statistical algorithm to get a close estimate of value in dynamic systems when the measurement tool has an inaccuracy. Kalman filter is a method based on recursive Bayesian filtering where the noise in the system is assumed Gaussian and used to estimate state based on linear dynamical systems in the state space format.

As described above Kalman filter trying to estimate state of the discrete time controlled process that is deal with linear stochastic difference equation. But what happens if process to be estimated is non-linear? A Kalman filter that linearizes the current mean and covariance is referred to as an extended Kalman filter. In estimation theory, the extended Kalman filter (EKF) is the nonlinear version of the Kalman filter which linearizes about an estimate of the current mean and covariance. In order to understand what an EKF is, we should know what a state space model and an observation model are.
The State Space Model: The state space model for our differential drive robot is as follows:

$$\begin{bmatrix} x_k \\ y_k \\ \gamma_k \end{bmatrix} = \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} x_{k-1} \\ y_{k-1} \\ \gamma_{k-1} \end{bmatrix} + \begin{bmatrix} \cos\gamma_{k-1} * dt & 0 & 0 \\ \sin\gamma_{k-1} * dt & 0 & 0 \\ 0 & 0 & dt \end{bmatrix} \begin{bmatrix} v_{k-1} \\ \omega_{k-1} \end{bmatrix} + \begin{bmatrix} noise_{k-1} \\ noise_{k-1} \\ noise_{k-1} \end{bmatrix}$$

Where v_{k-1} is the linear velocity of the robot in the robot's reference frame and ω_{k-1} is the angular velocity in the robot's reference frame.

If you know the current position of the robot (x,y), the orientation of the robot (yaw angle γ**)**, the linear velocity of the robot, the angular velocity of the robot, and the change in time from one timestep to the next, you can calculate the state of the robot at the next timestep.

Observation Model: An observation model is a mathematical equation that represents a vector of predicted sensor measurements y at time t as a function of the state of a robotic system x at time k, plus some sensor at time k, denoted by vector ω_k. In vector format, the observation model is:
Formal equation

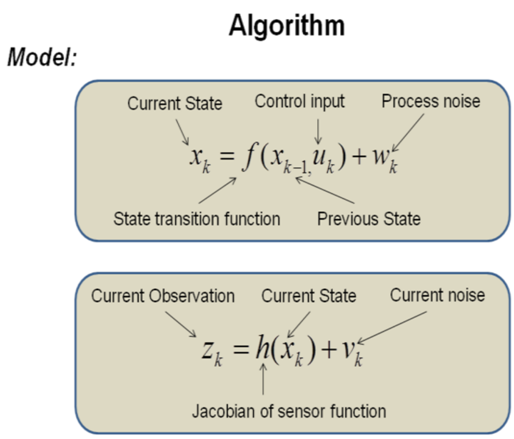
$$y_k = Hx_k + w_k$$

Because a mobile robot in 3D space has three states [x, y, yaw angle], in vector format, the observation model above becomes:

$$\begin{bmatrix} y_1^k \\ y_2^k \\ y_3^k \\ \cdot \\ \cdot \\ y_n^k \end{bmatrix} = H_{nx3}^t \begin{bmatrix} x_k \\ y_k \\ \gamma_k \end{bmatrix} + \begin{bmatrix} w_1^k \\ w_2^k \\ w_3^k \\ \cdot \\ \cdot \\ w_n^k \end{bmatrix}$$

Where, k = current time, y vector = n predicted sensor observations at time k, n = number of sensor observations, H = measurement matrix, w = the noise of each of the n sensor observations.
The Extended Kalman Filter is an algorithm that leverages our knowledge of the physics of motion of the system (i.e. the state space model) to make small adjustments to (i.e. to filter) the actual sensor measurements (i.e. what the robot's sensors actually observed) to reduce the amount of noise, and as a result, generate a better estimate of the state of a system.

STEP-1: Model



Here again is our modified formula for system state:

$$x_k = Ax_{k-1} + Bu_k$$

Where x is a vector and *A* is a matrix, u_k is a control signal and B is a coefficient to scale it.

$$z_k = Hx_k + v_k$$

Where z_k a measurement (observation, sensor) is signal and v_k is some noise added to that signal resulting from the sensor's inaccuracy.
The second equation tells that any measurement value is a linear combination of the signal value and the measurement noise. They are both considered to be Gaussian.

STEP 2 **-** Start Prediction

If you succeeded to fit your model into Kalman Filter, than the next step is to determine the necessary parameters and your initial values.
We have two distinct set of equations: Time Update and Measurement Update. Both equation sets are applied at each **kth** state.

Time Update *(prediction)*	**Measurement Update** *(correction)*
$x_k = Ax_{k-1} + Bu_k$ $P_k = F_{k-1}P_{k-1}F^T{}_{k-1} + Q_{k-1}$	$G_k = P_k H_k^T (H_k P_k H_k^T + R)^{-1}$ $\hat{x}_k = \hat{x}_k + G_k(z_k - h(\hat{x}_k))$ $P_k = (I - G_k H_k)P_k$

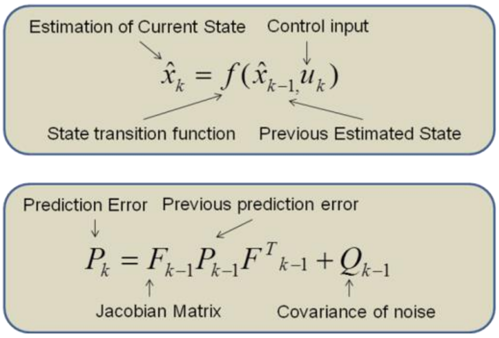
We made the modeling in STEP1, so we know the matrices A, B and H. Most probably, they will be numerical constants. And even most probably, they'll be equal to **1**. The most remaining painful thing is to determine R and Q. R is rather simple to find out, because, in general, we're quite sure about the noise in the environment. But finding out Q is not so obvious. And at this stage, I can't give you a specific method.

To start the process, we need to know the estimate of x_0, and P_0.

STEP 3 – Predict

After we gathered all the information we need and started the process, now we can iterate through the estimates. Keep in mind that the previous estimates will be the input for the current state. Here, $\hat{x}_k^-$ is the "prior estimate" which in a way means the rough estimate before the measurement update correction. And also P_k^- is the "prior error covariance". We use these "prior" values in our Measurement Update equations.

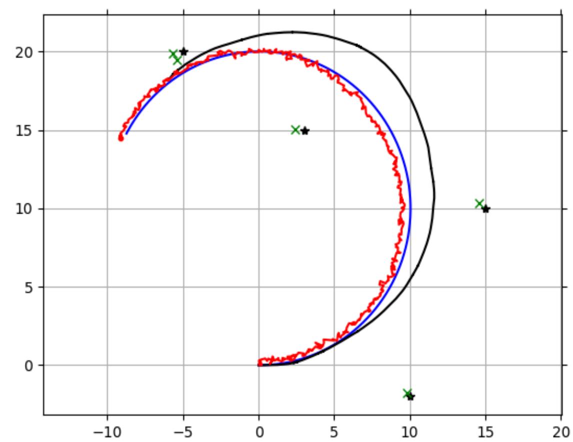
Predict:



In Measurement Update equations, we really find $\hat{x}_k$ which the estimate of x at time k is. Also, we find P_k which is necessary for the k 1*(future)* estimate, together with $\hat{x}_k$. The Kalman Gain (K_k) we evaluate is not needed for the next iteration step, it's a hidden, mysterious and the most important part of this set of equations. The values we evaluate at Measurement Update stage are also called "posterior" values. This also makes sense.

3. SIMULATION RESULT

Python simulation of mobile robot is performed using extended Kalman filter.



Where:

- Blue = True position
- Red = Estimated position
- Black = Observed position

4. CONCLUSIONS

In conclusion, EKF is a good way to implement SLAM because of its simplicity whereas probabilistic methods are complex but they handle uncertainty better. Using simulation shows the performance of this EKF algorithm and aids in the development of a robotic platform that has the capability to perform the localization and mapping of indoor environments in a cost effect manner. Simulation, using the robotic simulator stage, provided a platform to implement algorithm easily and to check the performance of the algorithm in a cost effective manner without an actual robot. Keeping in mind the end goal to utilize mobile robot for any application, robot should have a precise data. The PYTHON based simulation of indoor mobile robot is performed using Extended Kalman Filter. From python graph results, we conclude that the simulation is sufficiently accurate to be of use in developing indoor mobile robot using EKF SLAM algorithm.

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