

Vision and Simultaneous Localization and Mapping based Autonomous Indoor Mobile Robot

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Abstract— The Simultaneous Localization and Mapping (SLAM) has been one of the most studied subjects in Robotics. It is a fundamental process in mobile robotics, since it is responsible for building maps and at same time estimate the robot position in the environment. In this paper, a real-time implementation of simultaneous localization and mapping (SLAM) is described based on a mobile robot platform, which consists of two driving wheels, one caster wheel, an ultrasonic sensor and a Kinect sensor camera. The robot used for this purpose is differential drive robot. The main algorithm used is extended Kalman Filter (EKF) which is combined with Visual SLAM to handle data association problems and to map the trajectory with more accuracy. A mathematical equations of state space model and observation model is used to represents the motion of a robotic system from one timestep to the next and to infer what the sensor measurement would be at that timestep, respectively. The robot's built-in ability allows it to map the interiors of unknown environment and run autonomously using its self ruling and pilot feature. Robot Operating System is used for data processing and analysis of mobile robot platform. It is intended to implement the proposed SLAM by Extended Kalman Filter and VSLAM using low cost, energy efficient Raspberry PI as embedded system, IMU, laptop and ROS to verify the utility of proposed methods as a indoor wireless mobile robot.

Keywords— *Extended Kalman filter, State space model, Observation model, Robot operating system, differential drive robot*

I. INTRODUCTION

Wireless Mobile robots are very promising application of robotics. They should help people to deal with various tasks. The SLAM problem is the problem of acquiring a map of an unknown environment with a moving robot, while simultaneously localizing the robot relative to this map [1][2]. To solve this problem, there are several simultaneous localization and mapping (SLAM) approaches, such as Kalman filter-based algorithm [1][5][6], Particle filter[11], Graph based SLAM[12], G-mapping algorithm[12].

The idea of solving both of the mapping and localization problems simultaneously, firstly introduced by Smith et al. (1990) [1]. They developed a probabilistic method to indicate the spatial relationship between landmarks in an environment when robot is estimating its pose, currently. The map is represented as a set of landmark position and a covariance matrix is used to present the uncertainty of either the landmark or the robot's pose. This kind of map today is usually

mentioned as feature-based map, and this problem is called CML (Concurrent Mapping and Localization), but now more people would like to use SLAM (Simultaneous Localization and Mapping) [5]. Since then, a probabilistic approach [3] [4] [11] has become a standard way of solving the SLAM problem.

Kalman filters are an efficient algorithm and widely introduced to solve the SLAM [6]. However, the regular Kalman filter only can cope with linear problem, extended Kalman filter is a nonlinear version of the Kalman filter which linearizes about an estimate of the current mean and covariance [7]. Particle filter algorithm, also accomplish the target successfully [11]. However, in the presented paper the focus is given to the experimental results of an EKF-based localization of a mobile robot, which investigates a scalable algorithm for the simultaneous mapping and localization (SLAM) problem, and evaluates it in the context of unknown environment.

This paper is organized as follows. In Section II proposed robot system is described. Section III presents how the feature extraction and data association done with extended Kalman filter. Section IV describes Differential drive concept plan and mapping. Section V describes experimental results of robot in an indoor environment. The paper is concluded in Section VI.

II. PROPOSED ROBOT SYSTEM

The main task of proposed system is to collect indoor environment information and build environment map simultaneously without collisions in the whole process. Our developed Indoor mobile robot platform is illustrated in Fig. 1. It equips with sensors, Kinect Camera to grasp external information. The two wheels are driven by servo motors. Ultrasonic sensors are also called ping sensors, and are mainly used to measure the robot's distance from an object. The main application of ping sensors is to avoid obstacles. Proposed system includes Robot Operating System (ROS) to build map. ROS is a framework that is widely used in robotics. It provides a set of tools, libraries and drivers in order to help develop robot applications with hardware abstraction. In ROS, we are

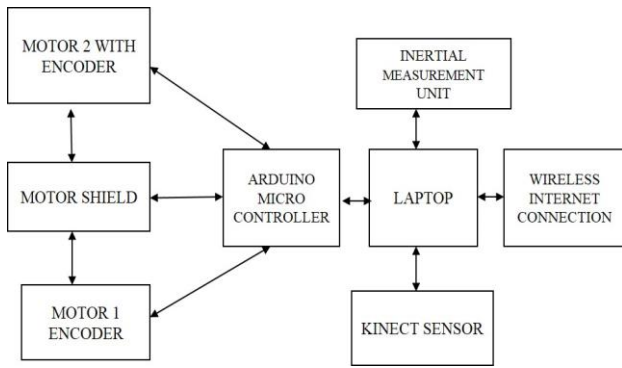


Fig. 1 Block Diagram Indoor Mobile robot

going to use two sensors of Kinect Camera namely the RGB camera and the depth sensor for vision and robotics tasks.

III. SIMULTANEOUS LOCALIZATION AND MAPPING

Simultaneous localization and mapping (SLAM) is a process which estimates the robot's pose and landmark's position at the same time, namely location and mapping. The fundamental step is to obtain external information to search proper features (landmarks). When navigating autonomously through an unknown environment, the robot keeps a track of its estimated (probabilistic) pose with reference to a global static frame usually located at its start point or a previous pose frame. The heart of our SLAM process is correlating the mean and covariance matrix of system state through EKF technique.

A. Extended Kalman Filter Algorithm for Localization

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:

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

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.

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 w_k . In vector format, the observation model is:

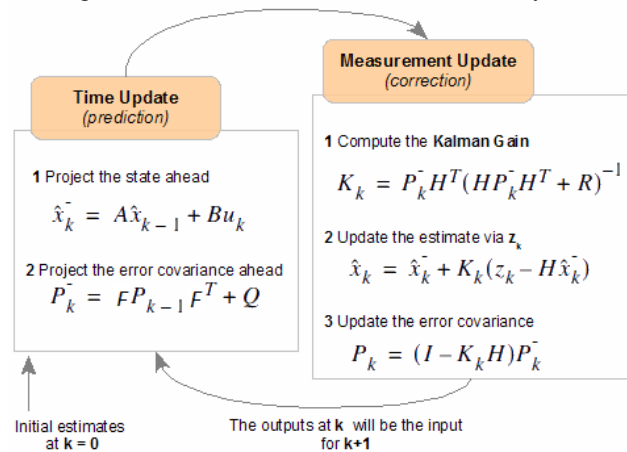
Formal equation

$$y_k = Hx_k + w_k$$

$$\begin{bmatrix} y_1^k \\ y_2^k \\ y_3^k \\ \vdots \\ y_n^k \end{bmatrix} = H_{n \times 3}^T \begin{bmatrix} x_k \\ y_k \\ \theta_k \end{bmatrix} + \begin{bmatrix} w_1^k \\ w_2^k \\ w_3^k \\ \vdots \\ w_n^k \end{bmatrix}$$

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.



Predict Step

- Using the state space model of the robotics system, predict the state estimate at time k based on the state estimate at time $k-1$ and the control input applied at time $k-1$.
- This is exactly what we did in my state space modeling.
- Predict the state covariance estimate based on the previous covariance and some noise.

Update (Correct) Step

- Calculate the difference between the actual sensor measurements at time k minus what the measurement model predicted the sensor measurements would be for the current timestep k .
- Calculate the measurement residual covariance.
- Calculate the near-optimal Kalman gain.
- Calculate an updated state estimate for time k .
- Update the state covariance estimate for time k .

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.

B. Simulation Result

Python simulation of mobile robot is performed using Extended Kalman Filter.

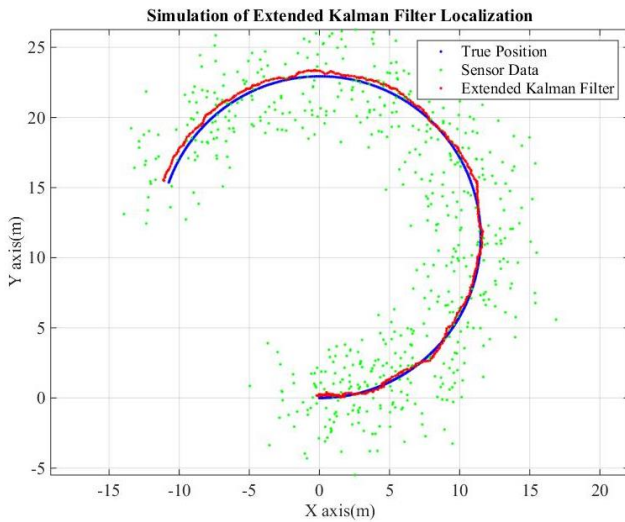


Fig. 2 EKF Localization

IV. DIFFERENTIAL DRIVE AND MAPPING

Differential Drive

Proposed mobile robots use a drive mechanism known as Differential drive. It consists of 2 drive wheels mounted on a common axis, And each wheel can independently being driven either forward or backward. While we can vary the velocity of each wheel, for the robot to perform rolling motion, the robot must rotate about a point that lies along their common left and right wheel axis. At any instance in time we can solve for R and ω :

$$R = \frac{1}{2} \left(\frac{V_l + V_r}{V_l - V_r} \right)$$

$$\omega = \frac{V_l - V_r}{l}$$

where l is the distance between the centers of the two wheels, V_r ; V_l are the right and left wheel velocities along the ground, and R is the signed distance from the instantaneous Center of Curvature (ICC) to the midpoint between the wheels.

Mapping

The ROS software in robots was connected to UI program in PC. Some main messages (topics) were communicated each other, for example, relative locations from robot to blocks, robot's location Depth data of Kinect sensor in robots was transformed to scan data at Ordroid of robot body. But RGB image and depth image were transmitted to PC and processed.

V. EXPERIMENT RESULTS

Following map is plotted using Kinect and ROS using g-mapping package of living room and passage between living room and bed room of our house.

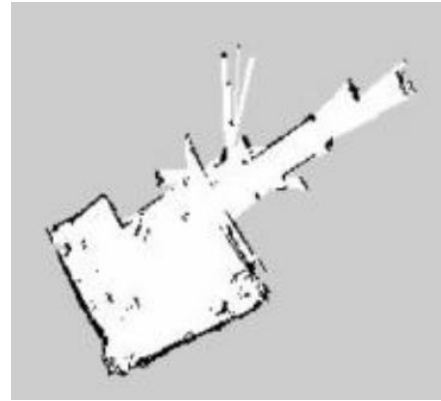


Fig. 3 Mapping & Localization

VI. CONCLUSION

As we can see from the results, system acts as we expected of it in real indoor environment. In SLAM (Simultaneous Localization and Mapping), by processing the detected features with landmarks which set previously in global coordinate system, we utilize Extended Kalman Filter to estimate the pose of robot. In the end, precise and usable map is provided to the end user. So, we expect that autonomous robots in unknown indoor environment would be possible easily without complex path planning.

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