Sensor fusion for prediction of orientation and position from obstacle using multiple IR sensors

An approach based on Kalman Filter

Rahul Sharma K, Daniel Honc, František Dušek

Department of Process control, Faculty of Electrical Engineering and Informatics,
University of Pardubice, Czech Republic,
rahul.sharma@student.upce.cz
{daniel.honc,frantisek.dusek}@upce.cz

***Abstract* – Kalman filters have gained immense research attention in robotics, throughout the last decades. Among the applications, localization of robots through Kalman filters proved promising results. This paper presents an application of sensor fusion for prediction of orientation and depth to wall/obstacle by fusing the inputs from three IR range finders. The experimental result demonstrates the capability of Kalman filter to predict the parameters precisely, from noisy sensor inputs. The technique find application in determining the position and orientation from wall which will be helpful in obstacle avoidance decision making, automatic parking of automobiles etc.**

Keywords- Localization, Kalman filter, obstacle avoidance, prediction.

I. Introduction

Localization and obstacle avoidance are the most challenging task for an autonomous robot. In many cases the robot perceives the environment with dedicated sensors, which often tends to be unreliable. Moreover, the robot has to deal with the uncertainty in sensor measurement error. Sensor fusion provides solution to these two problems by dealing with multiple sensor inputs.

Information from multiple sensors is fused together in sensor fusion techniques, thereby, estimating a more reliable perception of the environment. The fusion of sensor data can be from redundant sensors or complementary sensors. Sensor fusion has been applied in robot navigation applications [1,2]. [3, 4] presents a survey of various approaches in sensor fusion system.

Among the various approaches, Kalman filter have become a standard approach, using measurements from different sources for reducing errors in a least squares sense. A survey of Kalman filter is discussed in [5]. Kalman filter has been extensively used in robot navigation using GPS/INS sensor fusion [6]

This paper focuses on a simple sensor fusion technique, by Kalman filtering, of redundant sensors (IR range finder), in which data from multiple sensors are fused together to determine the two parameters, namely depth to the wall from the center of the robot and orientation to the wall. The sensor fusion is done in two stages, one Kalman filter for predicting the depth and the other one for predicting the orientation. Some application of the proposed method is also presented.

The paper is organized as follows: Section II describes mathematical modelling of the system followed by basics of Kalman filter in section III. The design of the proposed system is stated in section IV. Section V describes the experimental results and simulation followed by the conclusion.

II. Mathematical Modelling

(x_i, y_i) and (x_j, y_j) are the points on the line (wall), where the IR sensor beam gets reflected from the two sensors. The parameters of interest are d and $\emptyset$, where d is the perpendicular distance from the origin of the robot to the wall and $\emptyset$ is the angle between horizontal axis of robot and axis parallel to the wall.

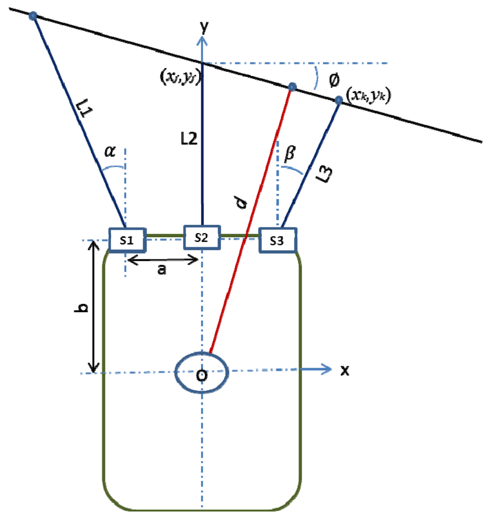

Fig 1. Robot configuration

S1, S2 and S3 are the three IR range finders connected to the robot. α and β are the angles at which the IR sensors are mounted on the robot. L_k is the depth to the wall from the robot measured by sensor k. a and b are the distances from the axes of robot to the sensors as shown in Fig. 1.The parameters can be derived from the following expressions [7].

$$\begin{bmatrix} x_i \\ x_j \\ y_i \\ y_j \end{bmatrix} = \begin{bmatrix} sin\alpha & 0 & 0 & 0 \\ 0 & sin\beta & 0 & 0 \\ 0 & 0 & cos\alpha & 0 \\ 0 & 0 & 0 & cos\beta \end{bmatrix} * \begin{bmatrix} L_i \\ L_j \\ L_i \\ L_j \end{bmatrix} + \begin{bmatrix} a \\ a \\ b \\ b \end{bmatrix} \quad (1)$$

$$\begin{bmatrix} y_i \\ y_j \end{bmatrix} = \begin{bmatrix} x_i & 1 \\ x_j & 1 \end{bmatrix} * \begin{bmatrix} m \\ n \end{bmatrix} \quad (2)$$

m and n are the slope and y intercept respectively. (2) can be written in the form of ,

$$Y = F * X \,, \quad (3)$$

Applying least square estimation (LSE) method to (3)

$$X = (F^T F)^{-1} F^T Y \quad (4)$$

$$\emptyset = \tan^{-1}(m) \quad (5)$$

$$\mathrm{d} = \frac{n}{\sqrt{1+m^2}} \quad (6)$$

From (1) to (6), the two parameters (d and Ø) can be found out from the depth measurement of the sensors.

III. Kalman filter

The Kalman filter is a set of mathematical equations that provides an efficient computational technique to estimate the states of a process by minimizing the mean of the squared error [8, 9]. The Kalman filter achieves this by estimating past, present, and even future states. Many variants of Kalman filter have been evolved over time. A discrete linear model Kalman filter is proposed in this paper for the parameter estimation. The two important steps of Kalman filter are prediction and update. The following are the important steps.

Prediction is governed by the following equations.

$$\hat{x}_k = F_k \hat{x}_{k-1} + B_{k-1} U_{k-1} \quad (7)$$

$$P_k = F_k P_{k-1} F_k{}^T + Q_{k-1} \quad (8)$$

Where F, B are the matrices which relates the previous state to current. $\hat{x}_k$ is the state variable vector. U_k , P_k and Q_k are control vector, covariance vector of state variable vector and process noise covariance.

Update stage is governed by the following equations.

$$y = Z_k - H\hat{x}_{k-1} \quad (9)$$

$$S = HPH^T + R \quad (10)$$

$$K = PH^T S^{-1} \quad (11)$$

$$\hat{x}_k = \hat{x}_{k-1} + Ky \quad (12)$$

$$P_k = (I - KH)P_{k-1} \quad (13)$$

Where Z, H, I, R are measurement vector, extraction matrix, unit vector and covariance vector of measurement vector respectively. K is the Kalman gain.

IV. Sensor fusion system

The raw analog signal from the IR sensors is preprocessed by acquiring a set of samples. From the set of samples, the mode (most repeating value, analog voltage in this case) of the data is calculated. The mode of the sample is then used to choose the sample set which falls in certain acceptable range (eg, ±5%) from the mode. Those chosen samples are averaged together and the depth is measured to get the inputs to the parameter estimation stage. The depth / distance measurement is done as presented in [7].

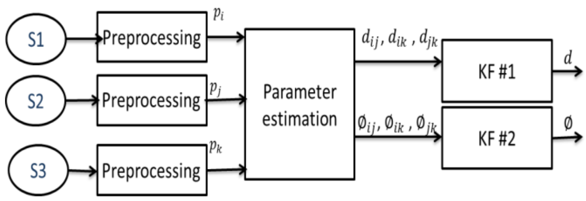

Fig.2. Sensor fusion system architecture

Fig 2 shows the stages in sensor fusion system employed in this paper. Pi, Pj and Pk are the depth measured from the sensor 1, 2 and 3 respectively. , Parameter estimation is done as explained in section II. Three sets of parameters are then fused together by Kalman filtering to predict the orientation and depth to wall. The two parameters are calculated by two different filters (KF#1 and KF#2).

For Kalman filter, KF#1, to predict the depth, the following are the Kalman filter parameters.

$$\hat{x}_k = \begin{bmatrix} x \\ \dot{x} \end{bmatrix}$$

Where $\hat{x}_k$ is the state variable vector. x is the distance to the wall and $\dot{x}$ is the velocity of the robot. The state transmission model is given by

$$F = \begin{bmatrix} 1 & \Delta t \\ 0 & 1 \end{bmatrix}$$

Δt is the sampling time. U_k , the move vector is assumed as null vector. The initial covariance matrix, P_k , can be expressed according to the level of uncertainty of the sensor data. The covariance matrix of measurement vector, R can be expressed as

$$R = \begin{bmatrix} \sigma_i & 0 & 0 \\ 0 & \sigma_j & 0 \\ 0 & 0 & \sigma_k \end{bmatrix}$$

Where σ_i, σ_j and σ_k are the variances of the three sensors 1, 2 and 3.The extraction matrix H can be expressed as

$$H = \begin{bmatrix} 1 & 0 \\ 1 & 0 \\ 1 & 0 \end{bmatrix}$$

For Kalman filter, KF#2, to predict the orientation, the following are the Kalman filter parameters.

$$\hat{x}_k = [x]$$

$$F = [1]$$

All other Kalman filter parameters of KF#2 are same as that of KF#1.

V. Results

A. Simulation

Simulation of Kalman filter has been carried out in MATLAB Simulink. Fig 3 shows the Simulink model used for simulation.

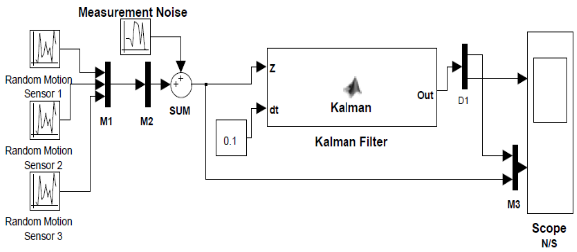

Fig 3: Simulation model

Fig 4 shows the output of the simulation. Covariance vector, P, has been initially assigned with high value, since the level of uncertainty in prediction is high. It was noticed that the covariance elements of vector P, have converged to low value.

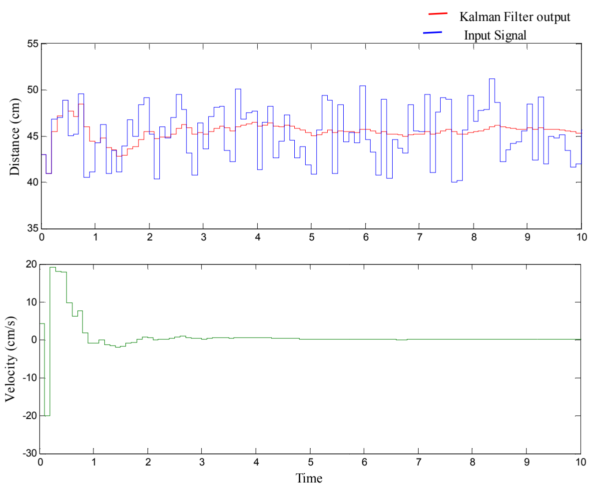

Fig 4: Output of simulation (position and velocity states Vs time)

B. Experimental Results

Three SHARP GP2Y0A02, IR range finders were interfaced to Arduino Due Board. The IR range finders were fixed on the front side of the robot with a=5, b=5, α=10□ and β=10□. The IR sensors were sampled at a rate of 1ms and the raw analog sensor data were first processed and the parameters were estimated. The three sets of parameters were then fused together by Kalman filtering.

The variances of the sensors were calculated experimentally. These variances were used in the R vector. The initial space vector x was assigned as null vector, since the starting point of the robot was not known. The covariance vector of X, P was assigned with high values, 1000, due to the high uncertainty in the measurement error. Fig 5 shows the experimental results of the sensor fusion technique. The output shows that the predictions of parameters (d and Ø) were closer to the actual value.

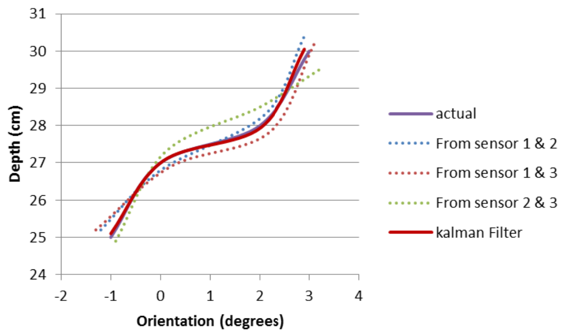

Fig 5: Experimental results

The proposed sensor fusion technique finds two applications. The measured parameters can be used in autonomous parking automobiles, where, the distance to wall and orientation are the most important requirement. The sensor fusion technique would help to give an accurate input to the motion control. The second application is obstacle avoidance decision making, where the orientation measurement would help the robot to make a right decision. For example, a positive value of Ø means a LEFT turn would be the right decision and vice versa.

Conculsion

The proposed system is modelled, simulated and tested in various environments. The data from multiple IR sensors were fused together to estimate the position and orientation of the robot by Kalman filtering. The fusion of multiple sensor inputs allows the robot to work in fault tolerant applications. The system finds applications in obstacle avoidance decision making, automatic parking of robots, localization (orientation estimate) of robots etc. When combined with absolute positioning sensors (GPS) or dead-reckoning sensors (IMU), the system can be further extended to real world applications in robotics

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