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# Localization of a Mobile Autonomous Robot using Extended Kalman Filter

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***Abstract*— This paper demonstrates an effective method for combining measurements from a gyroscope and rotary wheel encoders (odometry) in mobile robot localization. Sensor fusion of this kind is done using an Extended Kalman filter obtained from the values of above sensors for a mobile autonomous robot. Many such methods implement a statistical model that describes the behaviour of the gyroscope and the odometry component. However, because these systems are based on models, they cannot anticipate the unpredictable and potentially "catastrophic" effects of irregularities and frictional changes occasionally encountered on the floor. We present experimental evidence that non-systematic odometry error sources impact the robot's motion. Therefore a new approach has been developed based on a study of the physical interaction between ground and the robot. This approach has been implemented by developing an embedded system with ARM 7 based LPC2148 micro-controller. Experimental results show that the proposed method effectively reduces the localization error while yielding feasible parameter estimation.**

***Keywords-Localization, Extended Kalman Filter, Odometry, Gyroscope, Sensor Fusion, Autonomous Robot.***

## I. INTRODUCTION

Due to recent advancement in automation and robotics, use of automated machines is growing in industries; typically, packaging, automobile assembly lines, electronic hardware assembly and others. Any mobile robot must have a known state. The state refers to the current properties of the robot with respect to its environment. One of the most important state parameter is the position of the mobile robot. The mobile robot must know its position at every instant. This is localization of the robot.

In real world, localization of the robot is affected by various environmental noises, interferences and conditions that make this task tedious. These interferences act as the error sources, hence preventing the robot to know its position with precision and accuracy. A robot percept‘s its environment using sensors, which enables the robot to receive raw data about its environment and uses this data to determine its own position with respect to its environment. As these sensors directly interact with the surroundings, the noises occurring in the surrounding impact the readings of these sensors. So it is preferable to use multiple sensors, which increases the redundancy in the system, thus improving the probability of getting accurate data. Here we are using such multiple sensor fusion technique using the Extended Kalman filter to obtain precise localization. The Kalman filter fuses the readings from the different sensors and also predicts the next state of the robot. The current state is found by comparing the predicted value of the state and current observations. There are various other approaches for fusing the sensor data which are also discussed.

This paper demonstrates the development of an embedded system that makes use of odometry and gyroscope for accurate localization on the robot. Further, the advantages and disadvantages of the localization algorithm are studied.

## II. KALMAN FILTER

When using more than one sensor modality to obtain position orientation, such as a gyroscope and wheel encoders, an algorithm is needed to combine the readings to produce an accurate estimation of position. Typically a Kalman filter is used for this purpose. Kalman filter localization uses a Gaussian probability density representation of robot position and scan matching for localization. It represents the robot‘s belief state using a single, well-defined Gaussian probability density function, and thus retains just a μ and σ parameterization of the robot‘s belief about its position. This technique tracks the robot from an initially known position and is inherently both precise and efficient.

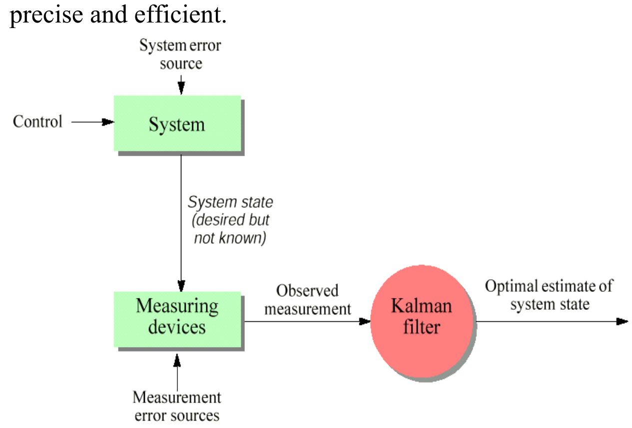


*Figure 1*. Basic Kalman implementation on a System

### A. Kalman Insufficiency:

However, Kalman filter itself is not adequate for global localization since it requires initially known position although the condition can be much relaxed, for example, by

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multiple hypothesis Kalman filters. Another difficulty in practical applications is that the optimal output of Kalman filter is based on the assumption that the system model is perfect and the process noises are white Gaussian. As a matter of fact, some modelling errors will always exist in the robot equation of motion and the mobile robot may have diverse disturbances during the exploration of environment which cannot be thought of as a white noise at all [2].

### B. *Extended Kalman Filter:*

The Extended Kalman Filter is used to overcome the problems with the basic Kalman approach. The Extended Kalman Filter provides a method for applying the Kalman Filter technique to a nonlinear problem by linearizing the estimation around the current estimate using partial derivatives. It also incorporates the trust factor user has on the different sensors used, by introducing their co-variances and measurement noise matrix.

The detailed equations for extended Kalman filter can be given as follows.

1. State Equation: For the Extended Kalman Filter, the process are governed by the non-linear stochastic difference equation

$$x = f(x) + w \tag{1}$$

Where $x$ is a vector of the system states and $f(x)$ is a nonlinear function of those states.

2. Measurement Equation: The measurement equation for the Extended Kalman Filter are considered a non-linear function of the states according to

$$z = h(x) + v \tag{2}$$

3. System and Measurement Noise: The system and measurement noise $v$ and $w$ for the Extended Kalman Filter are modeled as a random process with zero mean, which is similar to the system and measurement noise statistics modeled for a normal Kalman filter.
4. Filter Equations: In order to apply the continuous Ricatti equation, the non-linear system and measurement equations are linearised with a first order approximation using the Jacobian matrix.
   - F is the Jacobian matrix of partial derivatives of $f$ with respect to x, that is

$$F = \left.\frac{\partial f(x)}{\partial x}\right|_{x=\hat{x}} \tag{3}$$

-H is the Jacobian matrix of partial derivatives of $h$ with respect to x, that is

$$H = \left.\frac{\partial h(x)}{\partial x}\right|_{x=\hat{x}} \tag{4}$$

Now the optimal state estimate propagation from measurement time *ti-1* to measurement time *ti* can be represented with the following equations

$$\hat{x}(t_i^-) = f(x(t_{i-1}^+)) \tag{5}$$

$$P(t_i^-) = FP(t_{i-1}^+)F^T + Q \tag{6}$$

As before, when the state measurement *zi* becomes available at time *ti*, the estimate is updated by the following equations

$$k(t_i) = P(t_i^-)H^T(t_i)[H(t_i)P(t_i^-)H^T(t_i) + R(t_i)]^{-1} \tag{7}$$

$$\hat{x}(t_i^+) = \hat{x}(t_i^-) + k(t_i)[z_i - H(\hat{x}(t_i^-))] \tag{8}$$

$$P(t_i^+) = P(t_i^-) - k(t_i)H(t_i)P(t_i^-) \tag{9}$$

The linearization of the process will be valid and will produce excellent results if the estimate of the states is good. In cases where the state estimates are not good, the filter will diverge quickly and produce a very poor estimate.

## III. System Design

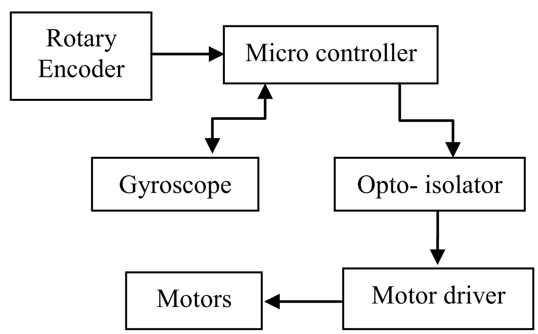


*Figure 2*. System Block Diagram

The microcontroller receives input from an encoder and a gyroscope. It processes this data and determines the current position of the robot in Cartesian coordinate system in real time. The motor driver circuitry along with its signal conditioning is responsible for the maneuvering of the robot. The Opto-isolator is used for the isolation of the drive unit from the logic unit of the microcontroller. The microcontroller is also responsible for giving the necessary drive commands to the motor driving circuitry, hence forth controlling the speed of the robot.

## IV. Implementation

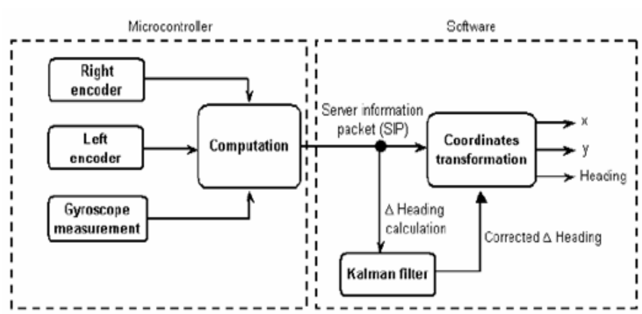


*Figure 3*. Kalman Filter Implementation

The Kalman Filter was implemented on LPC 2148 microcontroller, based on ARM 7 Processor core. The two sensors used were three channel optical shaft encoder of 500 PPR and ADIS16251 piezoelectric gyroscope.

### A. *Obtaining angular velocity from wheel encoders:*

The wheel encoders are capable of providing the number of pulses per rotation (ppr). The encoder so used is a 500 ppr encoder, so on the basis of Gray encoding, we get 4 counts for each rotation of encoder shaft. Hence the counts vs. wheel revolution relationship can be derived as:

1 pulse $\longrightarrow$ 4 counts

1 revolution $\longrightarrow$ 500 pulses

Therefore,

1 revolution $\longrightarrow$ 2000 counts

The counts from both the wheel encoders are now used to obtain the polar and Cartesian coordinates of the robot. The algorithm for the same is developed as follows:

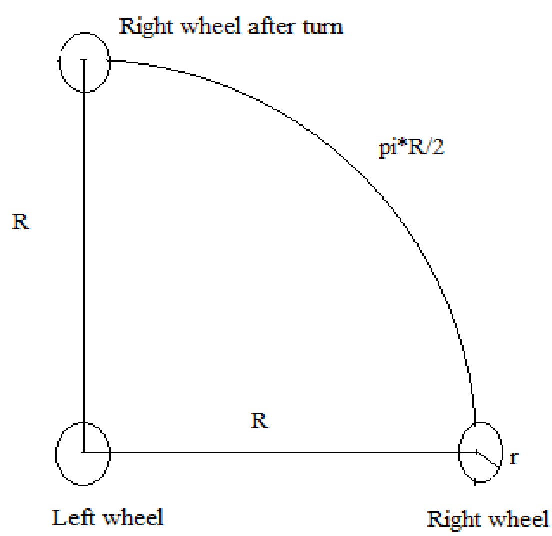


*Figure 4*. Angular velocity from encoders

Let the distance between the two wheels of the encoders be R, and the radius of each wheel be 'r'. With reference to the left wheel, we rotate the right wheel till the robot is perpendicular to the initial frame of reference. Distance moved by the right wheel = π*R/2. For 90° movement of the robot, distance moved = π*R/2. For, 1 rotation of the wheel, distance = 2π*r. So, for 90° movement of the robot, the number of rotations of wheel = R/4r. Now, 1 rotation of the wheel = 2000 counts. So R/4r rotations of wheel = 2000* R/4r counts. Hence 90° movement = 2000*R/4r counts. Or 1° movement = (2000*R)/ (90*4*r) counts. Hence, we establish the orientation vs. Counts relationship. As for the displacement of the robot in each instant of motion, suppose the counts from right wheel is C1 and the counts from the left wheel are C2. Then the instantaneous displacement (r) is = (C1-C2)/2. The Cartesian co-ordinates are then generated by these polar co-ordinates.

### B. *Obtaining angular velocity from Gyroscope:*

Integrate the gyroscope instantaneous reading with respect to time to get the angular velocity.

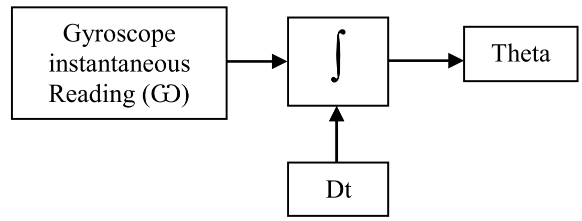


*Figure 5*. Angular velocity from Gyroscope

## V. Results

The Cartesian co-ordinate measurement was done using following two methods:

1. Two wheel-encoders only.
2. A gyroscope and a two wheel encoders fused via Extended Kalman Filter.

The experiment was conducted for both position estimation methods. The observations are as follows.

TABLE I. Observation Table of Cartesian Co-ordinates

| Sr. no | Actual co-ordinates (m.m.) | | Co-ordinates from Encoders only (m.m.) | | | | Co-ordinates from Kalman Sensor Fusion (m.m.) | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | X | Y | X | %X Error | Y | % Y Error | X | % X Error | Y | % Y Error |
| 1 | 50 | 0 | 53 | 6.00 | 10 | - | 51 | 2.00 | 6 | - |
| 2 | 70 | 20 | 65 | -7.14 | 32 | 60.00 | 68 | -2.86 | 24 | 20.00 |
| 3 | 100 | 50 | 92 | -8.00 | 59 | 18.00 | 95 | -5.00 | 52 | 4.00 |
| 4 | 100 | 100 | 96 | -4.00 | 116 | 16.00 | 96 | -4.00 | 106 | 6.00 |
| 5 | 150 | 100 | 161 | 7.33 | 107 | 7.00 | 154 | 2.67 | 102 | 2.00 |
| 6 | 150 | 120 | 155 | 3.33 | 133 | 10.83 | 154 | 2.67 | 127 | 5.83 |
| 7 | 200 | 150 | 217 | 8.50 | 158 | 5.33 | 206 | 3.00 | 155 | 3.33 |
| 8 | 200 | 200 | 212 | 6.00 | 222 | 11.00 | 208 | 4.00 | 211 | 5.50 |
| 9 | 250 | 200 | 243 | -2.80 | 226 | 13.00 | 247 | -1.20 | 213 | 6.50 |
| 10 | 250 | 250 | 247 | -1.20 | 249 | -0.40 | 247 | -1.20 | 248 | -0.80 |
| 11 | 300 | 250 | 291 | -3.00 | 257 | 2.80 | 294 | -2.00 | 255 | 2.00 |
| 12 | 350 | 350 | 336 | -4.00 | 368 | 5.14 | 342 | -2.29 | 357 | 2.00 |

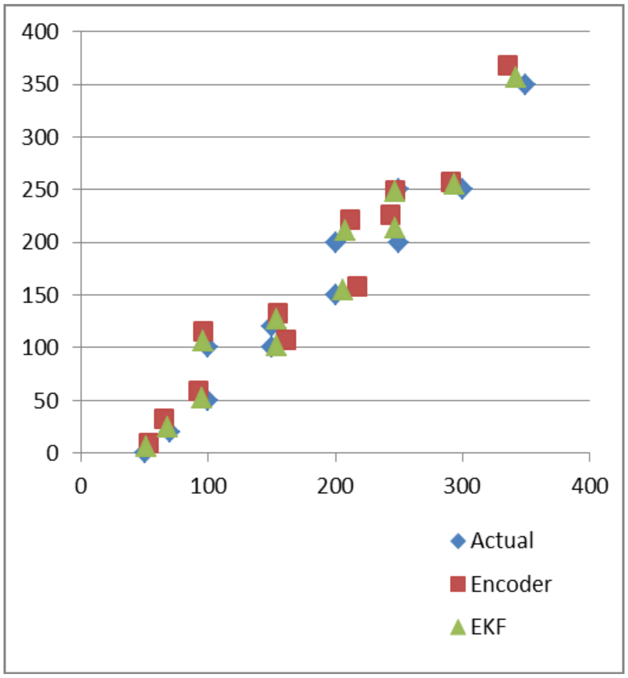


*Figure 6*. Comparison between actual, Encoder and Extended Kalman Filter readings.

TABLE II. AVERAGE PERCENTAGE ERRORS IN LOCALIZED SYSTEM

| **Positional Estimation Method** | **Percentage Error (%)** | |
|---|---|---|
| | X | Y |
| Localization using Two wheel encoders | 5.11 | 13.59 |
| Localization with sensor fusion by EKF | 2.74 | 5.27 |

## VI. OBSERVATIONS

It was found that the average percentage error is reduced considerably by this method, when compared to the results obtained from two encoders only. The reduction in errors is more eminent in the long run as the errors get accumulated in every state of the system, henceforth disturbing the next predicted state even more.

The filter is probabilistic in nature; hence it predicts the next state of the system and then performs a comparison of observations from the different sensors used. So a run time failure in any of the two sensors does not leads to complete disturbance of the system state. In such a scenario, the filter follows the less erroneous sensor, unlike any other mean or median filter, which would then lead the system to a completely incorrect position.

The observed difference in the average error for the X and Y axis is a result of lateral shift in the position of the robot due to uncontrolled motion. As the Y axis is perpendicular to the axis of rotation of the active and encoder wheels, any kind of lateral displacement in the position of the robot is left unmeasured by the encoders. While such a shift causes changes in the Y co-ordinate of the robot, but due to absence of steering and feedback from the wheels, the robot is unable to perceive this shift.

## VII. CONCLUSION

The performance and the error correcting capability of the Extended Kalman Filter are sufficiently higher as compared to the basic filter. Also the nominal errors existing after the application of filter are negligible and well within the tolerance level of the system.

Precise localization demands the use of various high performance sensors to read the environment. Due to the non-ideal nature of these sensors, errors are observed in the data obtained by them, hence dependence on any particular sensor alone, can be harmful to the system. So a minimum of two different sensors must be used to percept the environment at every instant.

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