

# Raspberry Pi GoPiGo Robot EKF SLAM Implementation

Gopal Menon  
Computer Science Department  
Utah State University  
Logan, Utah 84322  
Email: gopal.menon@aggiemail.usu.edu

**Abstract**—Robot motion is stochastic and not deterministic. A robot does not faithfully execute movement commands due to inaccuracies in its motion mechanism, approximations made in modeling its environment and incomplete modeling of the physics of its operating environment. Due to these reasons, the robot may not end up exactly at the location where it should have been if the movement command had been faithfully executed. The robot position may be thought of as a two dimensional probability distribution. This probability distribution will have a mean that will be equal to the expected robot location based on the movement command. The covariance will be the measure of how faithfully it executes commands. Due to this uncertainty in movement, with each motion command, the location uncertainty increases and after a while the robot gets lost. In some applications, robots need to be able to go into an unknown environment and explore it. This is a difficult problem due to the issue described above. If a map of the environment is available, the robot can use sensors to find its location in the environment. Conversely, if the robot knows where it is, it can generate an environment map. This is a sort of chicken and end problem. Simultaneous Localization and Mapping (SLAM) solves this problem. An Extended Kalman Filter (EKF) can be used to reduce robot location uncertainty. This document describes the implementation of EKF SLAM using a robot.

## I. INTRODUCTION

### A. The robot platform

The robot used for this implementation is based on a Raspberry Pi and is manufactured and sold by Dexter Industries [1]. The robot is equipped with an ultrasonic sensor that is capable of measuring distances accurately to 250 cm. The sensor is mounted on a servo mechanism that can point the sensor in any direction ahead of the robot. The robot moves through use of two wheels that can be independently controlled by motors. Each wheel has an encoder using which the robot can issue commands for a wheel to move a fixed number of steps. The robot also has a third castor wheel that can move in any direction, but is not powered. The robot will be given commands to make it move and it can sense its surroundings using the ultrasonic sensor.

### B. EKF SLAM

A Kalman filter is a gaussian filter algorithm that can use two gaussian distributions for a computed value and merge them together to form a distribution that has lesser variance than either of the two distributions. A Kalman filter however only works in the case of systems where the mechanics

are linear. This is where the Extended Kalman Filter (EKF) comes in. An EKF uses an approximation to find the resultant distribution after a prior distribution is transformed by a non-linear function.

The robot will compute its expected position based on its position and the movement command. It will also make independent measurements of its position using sensors. These two measurements will be combined through use of an EKF in such a way that the position uncertainty is reduced. The Kalman Gain or the reduction in the robot position uncertainty is inversely proportional to the sensor uncertainty. The better the sensor, the higher will be the Kalman Gain and the less uncertainty there will be in the robot position[5].

## II. PROBLEM DESCRIPTION

### A. The Bayes Filter

The Bayes Filter is an algorithm used for calculating beliefs[4]. In our case it is the belief of the robot position. This algorithm is used to compute the belief probability distribution  $bel$  from measurement and control data. The measurement data is obtained from sensors and the control data is obtained from the robot command or telemetry.

Bayes Rule says that

$$p(x|y) = \frac{p(y|x)p(x)}{p(y)} \quad (1)$$

Since the denominator in Bayes Rule does not depend on  $x$ , the factor  $\frac{1}{p(y)}$  can be written as  $\eta$ . So Bayes Rule in 1 can be written as

$$p(x|y) = \eta p(y|x)p(x) \quad (2)$$

Bayes Rule 1 can also be written as

$$p(x|y, z) = \frac{p(y|x, z)p(x|z)}{p(y|z)} \quad (3)$$

as long as  $p(y|z) > 0$ .

Applying 3 on the robot position  $x_t$  gives us

$$p(x_t|z_{1:t}, u_{1:t}) = \frac{p(z_t|x_t, z_{1:t-1}, u_{1:t})p(x_t|z_{1:t-1}, u_{1:t})}{p(z_t|z_{1:t-1}, u_{1:t})} \quad (4)$$

$$= \eta p(z_t|x_t, z_{1:t-1}, u_{1:t})p(x_t|z_{1:t-1}, u_{1:t})$$

Since the measurement  $z_t$  depends on position  $x_t$  and any past measurement  $z_{1:t}$  or command  $u_{1:t}$  does not provide any additional information on the measurement, we can say that

$$p(z_t|x_t, z_{1:t-1}, u_{1:t}) = p(z_t|x_t) \quad (5)$$

This allows us to simplify 4 as

$$p(x_t|z_{1:t}, u_{1:t}) = \eta p(z_t|x_t)p(x_t|z_{1:t-1}, u_{1:t}) \quad (6)$$

$$= \eta p(z_t|x_t)\overline{bel}(x_t)$$

where

$$\overline{bel}(x_t) = p(x_t|z_{1:t-1}, u_{1:t}) \quad (7)$$

Using the theorem of total probability

$$p(x) = \int p(x|y)p(y)dy \quad (8)$$

equation 7 can be written as

$$\overline{bel}(x_t) = \int p(x_t|x_{t-1}, z_{1:t-1}, u_{1:t})p(x_{t-1}|z_{1:t-1}, u_{1:t})dx_{t-1} \quad (9)$$

If we know the state  $x_{t-1}$ , past measurements and controls have no bearing on the state  $x_t$ . So

$$p(x_t|x_{t-1}, z_{1:t-1}, u_{1:t}) = p(x_t|x_{t-1}, u_t) \quad (10)$$

We can see that command  $u_t$  can be omitted from the set of conditioning variables in  $p(x_{t-1}|z_{1:t-1}, u_{1:t})$ . This gives us the recursive update equation 7 as

$$\overline{bel}(x_t) = \int p(x_t|x_{t-1}, u_t)p(x_{t-1}|z_{1:t-1}, u_{1:t-1})dx_{t-1} \quad (11)$$

This reduces to

$$\overline{bel}(x_t) = \int p(x_t|x_{t-1}, u_t)bel(x_{t-1})dx_{t-1} \quad (12)$$

## B. The Bayes Filter Algorithm

Based on the above mathematical derivation for a Bayes Filter, we can write down the Bayes Filter Algorithm as follows

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### Algorithm 1 Bayes Filter Algorithm

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1: procedure BAYESFILTERALGORITHM( $bel(x_{t-1}, u_t, z_t)$ )
2:   for all  $x_t$  do
3:      $\overline{bel}(x_t) = \int p(x_t|x_{t-1}, u_t)bel(x_{t-1})dx_{t-1}$ 
4:      $bel(x_t) = \eta p(z_t|x_t)\overline{bel}(x_t)$ 
5:   end for
6: end procedure

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The belief  $bel(x_t)$  at time  $t$  is computed from the belief  $bel(x_{t-1})$  at time  $t - 1$ . The input to the algorithm is the belief  $bel$  at time  $t - 1$ , along with the most recent control value  $u_t$  and the most recent measurement  $z_t$ . Its output is the belief  $bel(x_t)$  at time  $t$ .

The Bayes Filter Algorithm consist of two essentials steps. In line 3, which is the prediction step, it calculates its belief over state  $x_t$  based on the prior belief over state  $x_{t-1}$  and the control  $u_t$ . The belief  $\overline{bel}(x_t)$  that the robot assigns to state  $x_t$  is obtained by the integral (or in other words the sum) of the product of two distributions: the prior assigned to  $x_{t-1}$ , and the probability that control  $u_t$  induces a transition from  $x_{t-1}$  to  $x_t$ .

The second step of the Bayes Filter is called the measurement update. In line 4, the Bayes Filter algorithm multiplies the belief  $\overline{bel}(x_t)$  by the probability that the measurement  $z_t$  may have been observed. It does this for every hypothetical posterior state  $x_t$ .

## C. The Kalman Filter

The Kalman Filter is a technique for implementing a Bayes Filter[4]. This is used for filtering and prediction in linear Gaussian systems.

A probability distribution of a one-dimensional normal distribution with mean  $\mu$  and variance  $\sigma^2$  is given by the following Gaussian function

$$p(x) = (2\pi\sigma^2)^{-\frac{1}{2}} \exp \left\{ -\frac{1}{2} \frac{(x - \mu)^2}{\sigma^2} \right\} \quad (13)$$

The Normal distribution 13 is for a scalar  $x$ . In the case of a robot, the robot location on a flat surface is given by  $[x \ y \ \theta]^T$  where  $x$  is the x coordinate,  $y$  is the y coordinate and  $\theta$  is the robot orientation. This vector is called the robot pose. A Normal distribution over such a vector is called *multivariate*. These distributions have the following form

$$p(x) = \det(2\pi\Sigma)^{-\frac{1}{2}} \exp \left\{ -\frac{1}{2}(x - \mu)^T \Sigma^{-1}(x - \mu) \right\} \quad (14)$$

where  $\mu$  is the mean vector that has the same dimensionality as the state  $x$ .  $\Sigma$  is the covariance matrix and its dimension is the dimensionality of the state  $x$  squared. Equation 14 is a generalization of equation 13. Both definitions are equivalent if  $x$  is a scalar and value and  $\Sigma = \sigma^2$ .

For a Kalman filter, in posteriors are Gaussian if the following three properties hold

- 1) The state transition probability  $p(x_t|x_{t-1}, u_t)$  must be a linear function of its arguments with added Gaussian noise. This is expressed by the following equation

$$x_t = A_t x_{t-1} + B_t u_t + \varepsilon_t \quad (15)$$

where  $A_t$  and  $B_t$  are matrices.  $A_t$  has the dimension equal to the square of the state vector,  $B_t$  has the dimension of  $n \times m$ , where  $n$  is the dimension of the state vector and  $m$  is the dimension of the control variable  $u_t$ . The random variable  $\varepsilon_t$  models the uncertainty introduced by the state transition and depends on the robot mechanics. Its mean is zero and covariance will be denoted by  $R_t$ . The state transition probability distribution can be obtained by plugging in 15 into 14. The mean of the posterior state is given by  $A_t x_{t-1} + B_t u_t$  and the covariance by  $R_t$ .

- 2) The measurement probability  $p(z_t|x_t)$  must also be linear in its arguments with added Gaussian noise

$$z_t = C_t x_t + \delta_t \quad (16)$$

Here  $C_t$  is a matrix of size  $k \times n$ , where  $k$  is the dimension of the measurement vector  $z_t$ . The vector  $\delta_t$  describes the measurement noise. The distribution of  $\delta_t$  is a multivariate Gaussian with zero mean and covariance  $Q_t$ .

- 3) Finally the initial belief  $bel(x_0)$  must be normally distributed. We can denote the mean of this belief by mean  $\mu_0$  and covariance  $\Sigma_0$ .

The Kalman filter algorithm is given below

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**Algorithm 2** Kalman Filter Algorithm

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1:	<b>procedure</b>	KALMAN	FILTER	ALGO-
	RITHM( $\mu_{t-1}, \Sigma_{t-1}, u_t, z_t$ )			
2:	$\bar{\mu}_t = A_t \mu_{t-1} + B_t u_t$			
3:	$\bar{\Sigma}_t = A_t \Sigma_{t-1} A_t^T + R_t$			
4:	$K_t = \bar{\Sigma}_t C_t^T (C_t \bar{\Sigma}_t C_t^T + Q_t)^{-1}$			
5:	$\mu_t = \bar{\mu}_t + K_t (z_t - C_t \bar{\mu}_t)$			
6:	$\Sigma_t = (I - K_t C_t) \bar{\Sigma}_t$			
7:	return $\mu_t, \Sigma_t$			
8:	<b>end procedure</b>			

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The algorithm represents the belief  $bel(x_t)$  at time  $t$  by the mean  $\mu_t$  and covariance  $\Sigma_t$ . The input is the belief at time

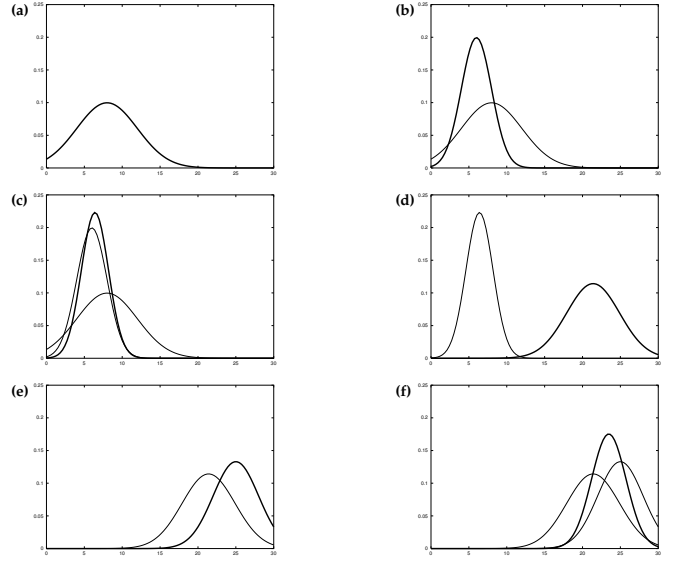


Fig. 1. Illustration of Kalman filters: (a) initial belief, (b) a measurement (in bold) with the associated uncertainty, (c) belief after integrating the measurement into the belief using the Kalman filter algorithm, (d) belief after motion to the right (which introduces uncertainty), (e) a new measurement with associated uncertainty, and (f) the resulting belief.

$t - 1$ , the control  $u_t$  and measurement  $z_t$ . The output is the belief at time  $t$ .

In lines 2 and 3, the predicted belief  $\bar{\mu}$  and  $\bar{\Sigma}$  is calculated representing the belief  $bel(x_t)$  one time step later, but before incorporating the measurement  $z_t$ . This belief is obtained by incorporating the control  $u_t$ . The mean is updated using the deterministic state transition function 15 with the mean  $\mu_{t-1}$  substituted for the state  $x_{t-1}$ . The update of the covariance considers the fact that states depend on the previous state through the linear matrix  $A_t$ . The variable  $K_t$  computed in line 4 is called *Kalman gain*. This is the reduction in uncertainty that is obtained by combining the prediction and correction steps. The belief  $bel(x_t)$  is transformed into the desired belief  $bel(x_t)$  in lines 5 and 6 by incorporating the measurement  $z_t$ . Line 5 manipulates the mean by adjusting it in proportion to the Kalman gain  $K_t$  and the deviation of the actual measurement  $z_t$  and the measurement predicted as per the measurement probability 16. Finally a new covariance of the posterior belief is calculated in line 6, adjusting for the information gain resulting from the measurement.

Figure 1 illustrates the Kalman filter for a simplistic one-dimensional localization scenario. Suppose the robot moves in the horizontal axis in each diagram in figure 1 with the prior over the robot localization given by the normal distribution shown in figure 1a. The robot queries its sensors on its location and these return a measurement that is centered at the peak of the bold Gaussian distribution in figure 1b. The peak corresponds to the value returned by the sensors and the its width or variance corresponds to

the uncertainty in measurement. Combining the prior with the measurement in lines 4 through 6 of the Kalman filter algorithm, yields the bold Gaussian in figure 1c. The belief's mean lies between the two original means, and its uncertainty width is smaller than both contributing Gaussians. This is the result of the information gain from using the Kalman filter.

Now let's assume that the robot moves towards the right. Its uncertainty grows due to the fact that the state transition is stochastic. Lines 2 and 3 of the Kalman filter algorithm provide us with the Gaussian shown in bold in figure 1d. This Gaussian is shifted by the amount the robot moved and is also wider because of the uncertainty introduced by the movement. The robot does a second sensor measurement shown by the bold Gaussian in figure 1e, which leads to the posterior shown in bold in figure 1f.

As this example illustrates, the Kalman filter alternates a measurement update step, in which sensor data is integrated into the present belief, with a prediction step, which modifies the belief. The prediction step increases and the update step decreases the uncertainty in the robot's belief.

#### D. The Extended Kalman Filter

The robot state transition function and landmark measurement probabilities are governed by nonlinear functions  $g$  and  $h$  respectively[4]:

$$x_t = g(u_t, x_{t-1}) + \epsilon_t \quad (17)$$

$$z_t = h(x_t) + \delta_t \quad (18)$$

Here  $x_t$  is the robot location at time  $t$ ,  $u_t$  is the robot command that causes it to reach position  $x_t$ ,  $z_t$  is the landmark measurement at time  $t$ ,  $\epsilon_t$  is the robot motion uncertainty that depends of the mechanical properties of the robot and  $\delta_t$  is the sensor measurement uncertainty.

### III. APPROACH/METHODS

#### IV. RESULTS

#### V. DISCUSSION

#### VI. FUTURE WORK

#### REFERENCES

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