Indoor Robot Localisation using Kalman Filter

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Abstract

Objective of this paper is to reduce the error in the estimation of the position of the robot. The localization of robot is a critical aspect in making them completely autonomous. Hence accuracy in estimating the position of the robot is of paramount importance. In order to make decisions without direct manual instructions the robot has to be aware of its position in the environment along with the situation at hand. For this effect the robots are built with sensors specifically designed to suit the need of the environment to gain feedback from the surrounding thereby obtaining data about its placement and the conditions around it. It is here that the problem of accuracy arises as there are uncertainties in both the feedback system as well as controlling system of the robot. To make a logical decision, the errors have to be minimized by optimally combining the data received from all the sources. The estimation theory provides us with a solution in the form of Kalman filter algorithm. It is an adaptive filter that combines uncertain data to obtain valid values of output required. It is seen that as SNR increases MSE in the position of the robot decreases thus accuracy increases. In this paper we concentrate on the issue of robot localization in closed space whose dimensions are previously known. We model the localization process as a linear phenomenon, as Kalman filter algorithm can only be used for linear systems. Using MATLAB Simulink we simulate our model to verify the concepts and validate the use of this filter in accurately determining the position of robot.

Keywords: Adaptive Filter, In-door Navigation, Indoor Robots Kalman Filter, Robot Localization

1. Introduction

Robots were originally made to reduce human effort in the fields where the work is repetitive and does not require active decision making. It is easier to have a pre-programmed machine to execute a set of actions repeatedly, as they are reliable and cheap. They can also work in environment that humans are not capable of working in. With advancement in technology we are now capable of making robots that can ‘think’. These robots are called autonomous robots. These robots are given certain tasks to complete by the user but the way to achieve the goal is determined by the robots itself, thus making it capable of taking decisions. This artificial intelligence is made possible by the use of fuzzy logic and neural networks. A mobile autonomous robot needs to be aware of its location to determine next sequence of actions. The process of determining the position of the robot in a closed space with predefined boundary is called in-door navigation. It is easier to model as there are less uncertainties in a well-defined confined space as compared to outdoor environment where a large number of parameters that can vary drastically. In door navigation is of two types: model-based methods and map-less methods. The model-based techniques strive to improve the position of robot by continuously modelling the filter parameters according to the inputs received. The map-less navigation techniques or the appearance-based navigation techniques seek to find the position of the robot by matching the view of current surrounding with the ones previously stored in the system. To make use of appearance based navigation techniques appropriate attributes of the image are to be selected that comprehensively represent the reference points. The drawback of the appearance-based navigation techniques is that it requires a powerful processor to extract meaningful data from the images and

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increases the complexity of solution. Though the technology for the same exists, it makes the process costly which is not user friendly. In-door navigation techniques are used for applications such as:
- Intelligent wheel chairs
- Vacuum cleaners
- Robot arms, Robotic manipulators (they have limited mobility)
- Mail delivery in an office setting
- Transports food/medicine in nursing homes to long term patients
- Tour guides in museums

In these applications the robot need to move in a closed well defined space. Though the boundary is well defined, the obstacles present in the space can’t be predetermined. The movement of other bodies in the place can’t be predicted as they all are random events. Thus the robot needs a method to avoid obstacles and prevent collision while performing the given task. We are going to use model-based navigation technique in our paper as they are better suited for coast effective applications.

2. Basics of Robot Localisation

To make logical decisions the robot must be aware of its current position as well as it should have the information about its final destination. The robot then determines a pathway to reach the said destination. The sensors are the devices that feed the robot with raw data from the environment which when processed gives the system a meaningful input. Based on the input received, a plan of action is made and then executed by the robot. It is from here that our problem arises. The different inputs received have to be processed along with their uncertainties to extract a conclusive output. The Kalman filter algorithm finds its usage here. It is a common data fusion algorithm which estimates stochastic state with minimum variance. Before we delve further into the algorithm, let’s have a look at how these decisions are made. The process of making decision takes in two phases - the data acquisition and path planning.

2.1 Data Acquisition

The sensors are like the eyes of the robot. They ‘see’ the world and guide the robot accordingly. There are different acquisition techniques that integrate the use of sensors that are used based on the need and the complexity of the system under consideration. In this scenario we need to measure the position and orientation of our robot as primary input data.

There are two types of measurement we can make - absolute and relative. The direct readings from the sensor give the absolute position of the device irrespective of its previous state. This is called exteroceptive measurement. It uses beacons and landmarks to map out the exact location of the robotic device in the environment. The robot has a prior information about the environment programmed into it along with the locations of all the landmark. A beacon sends an active signal to the robot which helps in realizing the absolute position of the device. The GPS also measures the absolute position of the robot in an environment. This is generally used in unbounded outdoor region of interest. The relative data measurement is called dead reckoning or proprioceptive measurement. Here the data is measured with respect to the starting point and do not consider any external input from the surrounding.

The most commonly used technique for relative position measuring is Odometer. It integrates differential increase in the position over time. By counting the number of revolutions of the wheel and multiplying it to the circumference of the wheel, it obtains the total distance travelled. This method is commonly used as it has good accuracy for short distances and is economically more viable. It has the added benefit of allowing large number of samples. The major disadvantage of this technique is the error margin in long distances and the orientation of the robot during the motion. The error occurs due to slippage and drift of the wheel, and it increases drastically when integrated over large interval of time. Also when traversing through surfaces that are not smooth the wheels deviate from the original path causing errors. The odometer doesn’t account for the irregularities in the surface of the floor.

Inertial navigation is yet another way of dead reckoning. The sensors generally used are a simple gyros and accelerometer. A gyros measures angular velocity relative to inertial space. More complex gyros can be used to improve the precision of the device. Few examples are laser gyroscope (that use Sagnac Effect) and MEMS gyros (that use Coriolis Effect) to achieve the same result.

Another effective localization technique is using active vision. This is beneficial when the environment is
completely unknown or vastly unpredictable. It can not only track the robot but also build a map of the area of interest. Such a process is called SLAM- Simultaneous Localization and Map Building\(^5\). In environments that change rapidly the distributive vision system\(^6\) is used to improve the topographical localization of the robot. Stereo Vision technique uses sound as a medium of guiding the robot to find its path\(^7,8\). Colour histograms are also used for tracking the robot in its environment\(^9\). When the map of the environment is already known ultrasonic sensors\(^10\) can be used for acquiring the required data. This technique is called interval analysis\(^11\). The ceiling pattern recognition\(^12\) method is an ingenious solution to indoor localization of the device.

### 2.2 Path Planning

It is here that the data collected by the sensors have to be processed to get a meaningful output. The most suitable pathway to the destination is determined before the actuators can implement it. Once the pathway is selected the decision making process is completed. To choose the best pathway out of the many possible routes to the desired destination we use a genetic algorithm along with Kalman filters\(^13\). It optimizes the solution without being influenced by the problem domain. The genetic algorithm\(^14\) fine tunes the predictions of kalman filter but are out of the scope of this paper.

### 3. Kalman Filter

The Kalman filter is a minimum variance estimator. It is a digital filter with recursive state- space model for stochastic estimation. It contains a set of mathematical equations that lends efficient computational means to estimate the state of a process, by reducing its mean square error. Basically, a Kalman Filter is a recursive data processing algorithm used for estimating the state of a linear dynamic system that is contaminated by noise. The fundamental advantage of this filter is that the system need not be accurately modelled. The filter adapts to the changes in the model and predicts the future value of the process with a very less margin for error. Also the Kalman filter does not require the assumption that all errors have Gaussian distribution. In case of Gaussian noise distribution the filter results are very accurate and have same conditional probability estimate.

### 3.1 A Brief History

The filter algorithm was co- developed by a Hungarian mathematician cum electrical engineer in. A more generalized version that also accounts for non-linear systems is called extended Kalman filter. It was developed by a mathematician named in. Historically the first ever application of this filter was in the Apollo space mission in 1960s.

### 3.2 The Applications

The Kalman algorithm finds its application in a vast number of fields.

- Tracking Objects
- Navigation
- Economic models
- In computer vision
- Fitting Beizer patches to point data
- Disparity integration

### 3.3 The Algorithm

The algorithm contains of two parts; the estimate and the update. The equations for estimate are:

\[
\hat{X}_k = A\hat{X}_{k-1} + BU_{k-1} + W_{k-1}
\]

\[
P_{\hat{X}} = AP_{\hat{X}-1}A^T + Q
\]

The equations for update are:

\[
X_{k+1} = X_k + K(Z_k - HX_k)
\]

\[
K_k = P_kH^T(HP_kH^T + R)^{-1}
\]

\[
P_K = (I - K_kH)P^-K
\]

Where

- \(X_k\): The Estimated Output
- \(X_{k-1}\): The Previous Estimated Output
- \(U_k\): The Input Parameters
- \(P_k\): The Predicted State Variance Matrix
- \(P^-\): The Measured State Variance Matrix
- \(P_{k-1}\): The Priori State Variance Matrix
- \(K_k\): The Kalman Filter Gain
- \(X_k\): The Measured Output
- \(Z_k\): The Actual Output
- \(A\): The Transition Matrix
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B : The control Matrix  
H : The measurement Matrix  
Q : The process variance matrix  
R : The measurement Noise Matrix

The estimation equations predict an output of the process under consideration. The update equations find the difference between the actual outcomes and the predicted outcomes. The variables and their corresponding matrices are then updated so as to reduce the error in estimation. These values are then used for the prediction of next value. This cycle continues till the prediction is accurate. The more the execution of the prediction-update cycle, the more is the precision of obtained estimates.

In the indoor robot localization problem the process variance matrix (Q) is taken to be a small value as we assume that modelling the room accurately does not present a great challenge and that the variations in a closed environment are not large. The value of state variance matrix (P) is taken initially to a large number as the state i.e. the position of the robot is completely unknown. Within the first cycle of algorithm this value is reduced drastically as the filter adapts to with respect to the inputs taken from the surrounding. But the prior estimate is 0 here as the first input is given only when the program starts to run. The control parameters and the control matrix is not considered here as we are trying to avoid any external controlling factor thus making the localization process autonomous. The measurement variance matrix is taken according to the precision of the sensors used for measuring the input data. Here we assume that the sensors are accurate and do not induce large error in the readings. The state transition matrix (A) is obtained from the approximate differential equation of the state modelled. The measurement matrix (H) is the mapping factor. It scales the input by a standard value for the ease of computation. Here we take that as an identity matrix as scaling factor.

We generate random input from MATLAB Simulink and verify the accuracy of our model. The output contains three parameters- the 2-D co-ordinates of the floor and the orientation of the robot with a fixed reference.

\[
B = \begin{bmatrix} 1 & 0 & 1 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix}
\]

\[
H = \begin{bmatrix} 1 & 0 & 1 \\ 0 & 1 & 1 \\ 0 & 0 & 1 \end{bmatrix}
\]

\[
A = \begin{bmatrix} 1 & 0 & 1 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix}
\]

\[
I = \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix}
\]

\[
Q = 10^{-6}
\]

\[
R = 2*10^{-6}
\]

\[
P, B, u \text{ are all zeroes as they are insignificant in our case, so are not coded into the program. Substituting the matrix values in the algorithmic equations, we obtain the remaining unknown parameters. The Kalman gain parameter } K \text{ is obtained from the estimate part of the first cycle. Running the code gives the graph between SNR and MSE of the model. From Figure 1 we see that the MSE generally reduces as the SNR value increases. Now that we have verified that our Kalman filter is suitable for the task, a MATLAB code for running it on a large scale is simulated and the graph between the estimated output of the process and the actual output of the process is obtained for analysis. The output obtained is in three different graphs; the X-coordinate as shown in Figure 2, the Y-coordinate as shown in Figure 3 and the angle of inclination from X-axis as shown in Figure 4. The data from the three graphs are compiled for each instance in time to get the location of the robot.}

Figure 1. SNR vs MSE plot.
The following three graphs are sample output obtained:
The blue line indicates the actual output while the orange shows the Kalman predictions. Notice how the lines almost coincide as the number of sample increases. Thus we obtain the location of a robot placed in a particular environment with help of the kalman algorithm.

4. Conclusion

Thus using the Kalman model reduces the mean square error in determining the position of the robot. Once the localization process is complete the robot gets an idea of its position with respect to the surrounding it proceeds to carry out the task assigned to it. Further decision making involves fuzzy logics and neural networks.

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