Mobile Robot using Kalman Filter for Localization

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Abstract: This research investigates using a Kalman filter to enhance the mobile robot localization. Accurate localization is crucial for effective steering and successful mission completion in the autonomous robotic systems. The Traditional methods encounter problems comes from the noise and the errors in sensor measurements, resulting in the failure in performance. The Kalman filter is a mathematical method that may guess the state of the dynamic system depend upon a sequence of noisy and the incomplete explanations. It is a consistent technique to address localization issues. The Kalman filter, a method for the iterative state estimation, significantly improves the localization precision of a two-wheeled (2WD) robot. The experimental outcomes display that the filter decreases uncertainty and enhance the robot's ability to cross the complex conditions. A Simulink application permits fast modeling and simulation of the robot's dynamic performance, giving valuable visions into perfect filter limitations. This research aims to improve the robotics arena by indicating a dependable method for the localization, which is vital for an autonomous steering and the mission execution. The numerical analysis has a significantly improves the robot's capacity to steer in the noisy environments, rendering it a possible explanation for the real-time applications in the dynamic situations.

Keywords: Localization, Kalman Filter, Mobile Robot, Simulations, Simulink.

1. Introduction

In recent years, researchers have been very interested in the fields of the localization and navigation for autonomous robots. Mobile robots are highly capable of locating with high accuracy and effectively navigating their surroundings which is essential for enabling independent and intelligent robotic systems.

The Localization problem is a major challenge for mobile robots due to their effective and critical role as a fundamental requirement for the high-level tasks [1]. Furthermore, the mobile robot localization frequently encounters accuracy and precision issues, it is commonly referred to as position tracking or position estimation [2][3] [4].

One of the most important problems facing robots is positioning, which requires an actual estimate of the robots situation. Therefore, it requires combining the data acquired by different [5]. To obtain high accuracy in the representation of the position of the robot, an integrated and decisive process must be available to overcome the uncertainty. The state of the robot is estimated by the comprehensive analysis of the sensory data processed, collected and then integrated by the sensors of the robot when executing in the case of non-contact with the Kalman filter [6][4]. There is a great challenge in locating the mobile robot, and in turn it faces obstacles in closed environment conditions such as internal data, so it is necessary to focus on the importance of determining the flow line or route of the robot. Positioning is considered as a key milestone in mobile robot navigation, as it is a key element that requires the combination of data processing or information related to positioning and representation as well as the surrounding environment. Therefore, the problem of robot navigation involves three main factors (self-positioning, building maps, and finally route planning [7] [8].

The accuracy of sensors employed in mobile robot localization can be influenced by multiple factors, such as internal sensor interference and external environmental noise. These errors can have a substantial impact on the reliability and effectiveness of the localization process [9][10]. To ease these challenges and improve mobile robot localization, filtering methods are commonly employed. Among the various factors that influence the performance of robotic systems, Kalman filters have proven to be effective in addressing uncertainties in multiple aspects such as robot localization, navigation, following, tracking, motion control, estimation, and prediction [11].

Over time, numerous variations of Kalman filters have been developed to cater to specific requirements and scenarios. Accordingly, over the past 30 years, extended Kalman filters (EKF) and unscented Kalman filters (UKF) have emerged as popular variations of the traditional Kalman filter, demonstrating their capability to solve various localization problems. These filters have found applications in diverse areas such as target tracking, localization, mapping, and navigation [12][13]. The Kalman Filter has several applications such as tracking moving objects and predicting stock prices. The algorithm is named after Rudolf Kalman, a Hungarian-American mathematician and electrical engineer, who first proposed it in 1960 [4] [14].

Kalman Filter is a mathematical algorithm used for data filtering, smoothing, and prediction in various fields such as engineering, finance, and robotics. It works in linear systems [15]. It is a recursive algorithm that uses a series of measurements over time to estimate the state of a system and then uses this estimate to make predictions about the future state [16]. The Kalman filter algorithm is efficient and most widely used due to its ability to handle the noisy measurements and adapt to changes in the system being measured.

Since the introduction of Kalman filtering, the term "filter" has come to signify more than just the process of separating the constituent parts of a mixture. In the context of Kalman filtering, the term now encompasses the solution of an inversion problem. These involve understanding how measurable variables represent functions of the primary interest variables. Kalman filtering, in essence, performs an inversion of this functional relationship, estimating the independent variables as inverted functions of the dependent variables[18]. Moreover, the variables of interest can exhibit dynamic behaviour with only partially predictable dynamics.

According to[19] [20] [21], Kalman filtering finds frequent applications not only in state estimation but also in forecasting various system applications, such as weather prediction, stock market analysis, and more. The versatility of Kalman filtering extends beyond engineering domains, as it has also been employed in non-engineering applications like short-term forecasting and the analysis of life lengths derived from dose-response tests in recent years. Moreover,[22] emphasizes that the Kalman filter holds significant importance as it can adapt itself to nonstationary environments. Furthermore, as mentioned in [19], the Kalman filter offers support for estimations of past, present, and future states, even in cases where the exact nature of the modelled system is unknown. Through a set of mathematical equations, the Kalman filter provides an efficient computational approach to estimating the state of a process while minimizing the error [23][24].

As stated in [25], some systems can only be adequately represented with finite parameters. Recognizing this limitation, R.E. Kalman developed an optimal state estimator, the Kalman filter, specifically designed for linear estimation of dynamic systems utilizing the state space concept. Accordingly, the Kalman filter exhibits remarkable capabilities in several respects. It serves as an optimal observer, generating estimates of the system states that are unbiased and have minimum variance. This means that, on average, the error between the Kalman filter's estimate and the true state of the system is expected to be zero, and the expected value of the squared error between the actual and estimated states is minimized. Kalman filter is regarded as an efficient recursive filter algorithm that plays a crucial role in estimating the state of a dynamic system based on a sequence of noisy measurements [25][26]. It can be a sequential minimum mean square error (MSE) estimator that considers the additive noise present in the measurements and estimates the covariance of the estimate can be seen as a sequential minimum mean square error (MSE) estimator that takes into account the additive noise present in the measurements, along with estimating the covariance of the estimate [4]. This paper presents the implementation of the Kalman filter to enhance mobile robot localization to estimate mobile robot location using Simulink. The rest of this paper is organized as follows: Methodology, which contains the Kalman filter algorithm and Kalman filter modelling in Section 2. Section 3 discusses the Kalman filter using the Simulink program, the limitations of the Kalman filter algorithm, and the advantages of the Kalman filter in results and discussions. Section 4 presents the conclusion of this work.

2. Methodology

2.1 Kalman Filter Algorithm

The Kalman filter is an iterative algorithm that updates its estimate of the system state as new data becomes available and is commonly used in many different applications, such as navigation, control systems, and signal processing [22].

The Kalman Filter algorithm flowchart is depicted in Figure 1. This algorithm encompasses a series of steps that facilitate the estimation and prediction of system states. The key steps of the Kalman filter can be summarized as follows: The process commences with the initialization phase. During this step, the initial values for the state vector, denoted as x0, and the error covariance matrix, denoted as P0, are set. Following the initialization phase, the Kalman Filter algorithm proceeds to calculate the predicted values based on either the initialized values (at the first time step) or the previously estimated values. Utilizing these predicted values obtained in the previous step, the Kalman gain (K) is computed. At this point, a new measurement becomes available, and the Kalman gain is recalculated to incorporate this new information. The current step involves the computation of the estimated value, considering the predicted values and the Kalman gain.

These steps are as follows:

Initialization: The algorithm starts with an initial estimate of the system state and its covariance matrix, which represents the uncertainty in the estimate.

Prediction: The Kalman filter forecasts the upcoming state of the system depend upon the existing state guess and the system model. The prediction moreover contains a guess of the covariance matrix of the prediction error.

Update Measurement: Based on the recent measurement and the anticipated measurement from the system model, the Kalman filter modifies the state estimate. The forecast and measurement are averaged using a weighted method in this update; the weights are determined by the degree of uncertainty in the prediction and measurement. Additionally, upon obtaining a new measurement, the estimate of the state and covariance matrices is updated. Furthermore, the update process computes the Kalman gain as a weighted sum of the measurement and the anticipated state by using the observation model. Therefore, in order to modify the anticipated state in light of the new measurement data, the Kalman gain is essential. The estimate of the state is improved by adding the measurement using the Kalman gain. In addition, taking into account the integration of the new measurement data, the covariance matrix is adjusted to reflect the decreased uncertainty in the estimate[27] [28]..

Repeat: Every time a new measurement is obtained, the prediction and update procedures are performed recursively, updating the state and covariance matrices in light of the new data [22] [25].
The formulations of Kalman filter algorithm are as follow:
Initialization:

$$\hat{\mathbf{x}}_0 = \mathbf{x}_0 \quad ,$$

$$P_0 = \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix} , \quad R = \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix}$$

Predict:

$$\hat{\mathbf{x}}_{k+1} = f\left(\mathbf{x}_k, \mathbf{u}_k\right)$$

$$\mathbf{P}_{k+1} = F_k \mathbf{P}_k F_k^T$$

Update:

$$\mathbf{y}_{k+1} = \mathbf{z}_k - \hat{\mathbf{x}}_{k+1}$$

$$\mathbf{S}_{k+1} = H_k \mathbf{P}_{k+1} H_k^T + R$$

$$\mathbf{K}_{k+1} = \mathbf{P}_{k+1} H_k^T \mathbf{S}_{k+1}^{-1}$$

$$\hat{\mathbf{x}}_{k+1} = \hat{\mathbf{x}}_{k+1} + \mathbf{K}_{k+1} \mathbf{y}_{k+1}$$

$$\mathbf{P}_{k+1} = \left(\mathbf{I} - \mathbf{K}_{k+1} H_k\right) \mathbf{P}_{k+1}$$

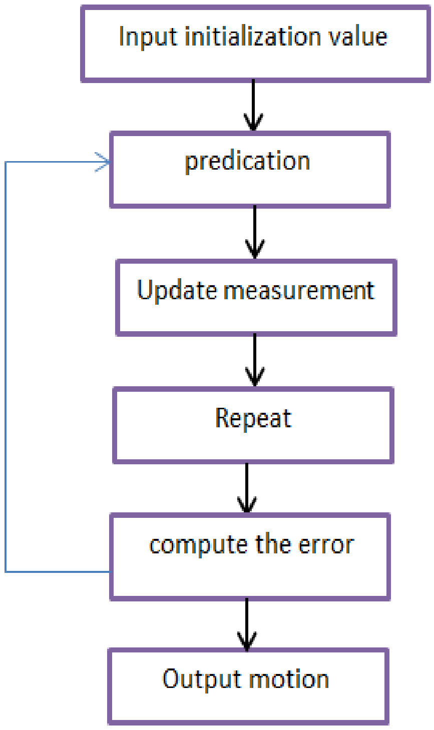


Figure 1. Kalman filter algorithm flowchart

Generally, the Kalman filter reduces the mean square error, making it an optimal estimator between the true system state and its estimate, given the available measurements and the system model. The filter uses a probabilistic model and the measurements, which allows it to handle noise and uncertainty in an efficient and effective way [29][17].
There are two sets of equations that are used in the Kalman filter, represented in Table 1.

Table 1 Kalman filter equations

Time update (predictor) equations	The aforementioned equations play an essential role in projecting the current state, and error covariance is estimations forward in time. This projection enables the derivation of a priori estimations for the subsequent time step.
Measurement update (corrector) equations	These equations are crucial for the feedback process within the Kalman Filter algorithm. They enable the a priori estimate to include a new measurement, which enhances the a posteriori estimate.

The estimation process begins by initially estimating the state of the system at a certain time. Subsequently, feedback is obtained in the form of measurements.

2.2 Kalman Filter Modelling

Kalman filter is a mathematical process that estimates and forecasts a system's state across time in the presence of noise and uncertainty. The process is divided into two independent stages: the prediction stage computes the state variables and their current uncertainty, and the update phase modifies the computations based on fresh measurement data. The efficacy of this filter is recognized in several tracking and data prediction applications, with navigation, robotics, and signal processing

The Kalman filter is based on the theoretical model that assumes a linear dynamic system with Gaussian noise by using Matlab. It uses pre-existing knowledge of the system to make predictions about a process's state as time progresses. The Kalman filter's efficacy is determined by its precision; if the model accurately represents the real-world system, the filter achieves the most accurate state estimation. Developing appropriate linear models for Kalman filters is essential when utilizing sensor data in different applications.

Figure 2 depicts a Simulink program illustrating the utilization of the Kalman filter in conjunction with sensor readings. The input data is obtained from the sensor's measurements, and subsequently, the Kalman filter is employed to effectively filter out noise from both the x and y values.

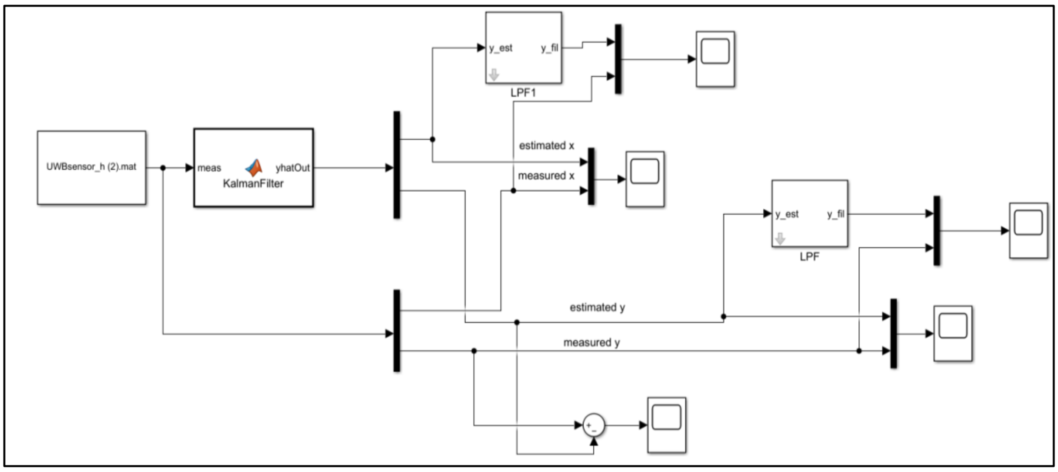


Figure 2 Kalman filter by using sensor’s data in Simulink

3. Results and discussions

When you use a Kalman filter in Simulink, the results and discussion are usually about how well the filter guesses the states of a state-space model given data on the process and measurement noise. The Kalman Filter in a Simulink model can visually illustrate its feedback mechanism, assisting users in understanding the recognition of measured and unmeasured states based on process input. We can compare the estimated and actual states to assess the filter's performance in real-time applications.

Figure 3 displays graphs illustrating the estimated values for the x and y coordinates, respectively. The blue line represents the sensor's data, while the red line represents the estimated values obtained through the utilization of the Kalman filter.

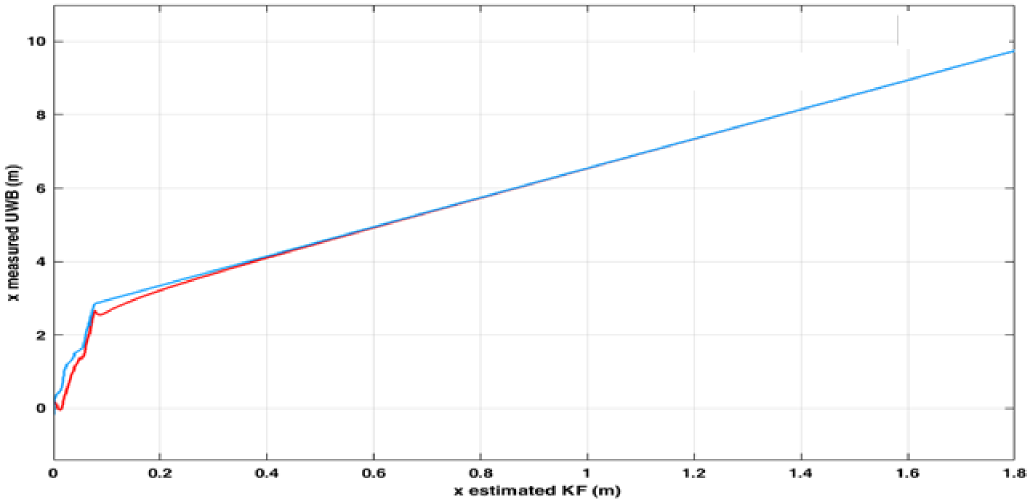


Figure 3 Kalman filter by using sensor’s data for x

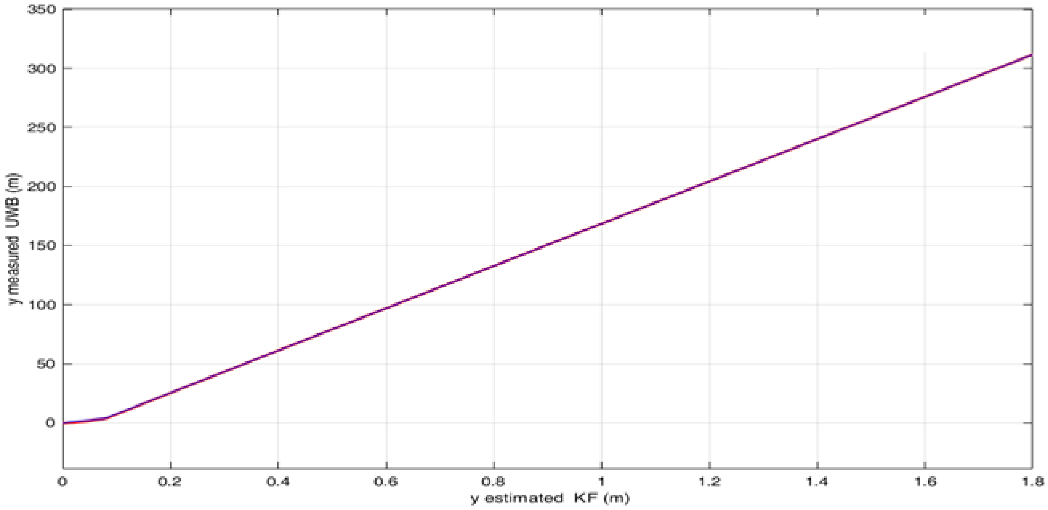
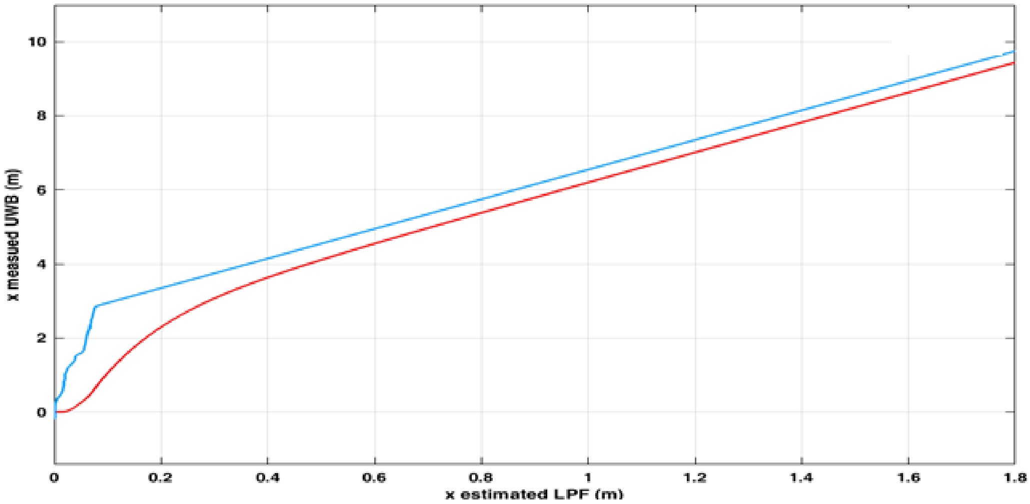
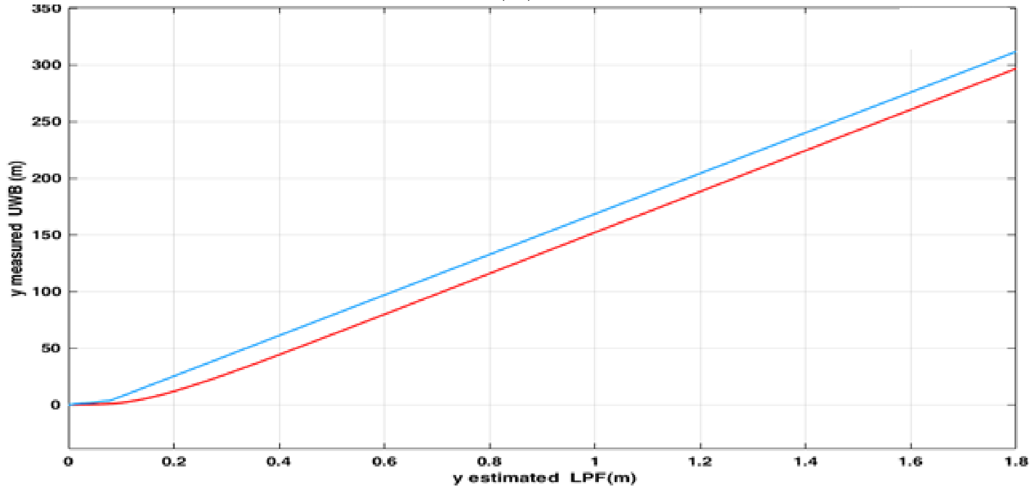


Figure 4 Kalman filter by using sensor’s data for y

Figure 5 depicts the utilization of a low-pass filter (LPF) in conjunction with the Kalman filter in the experimental setup. The LPF is configured with a frequency of 10 and a time delay of 0.001s. In the graphs, the blue line represents the raw sensor data collected during the work. The red line illustrates the estimated data obtained through the combined implementation of the Kalman filter and LPF. Subsequently, the estimated data for the x-axis undergoes another round of noise removal using the Kalman filter. Finally, the filtered data for both the x and y axes is passed through the LPF again. Figure 5(b) specifically demonstrates this process for the y-axis.



(a)



(b)

Figure 5 Kalman filter by using sensor's data (a (x), (b) (y))

Figure 6 shows the relation between the actual and estimated values, which is used to illustrate the error through the Kalman filter.

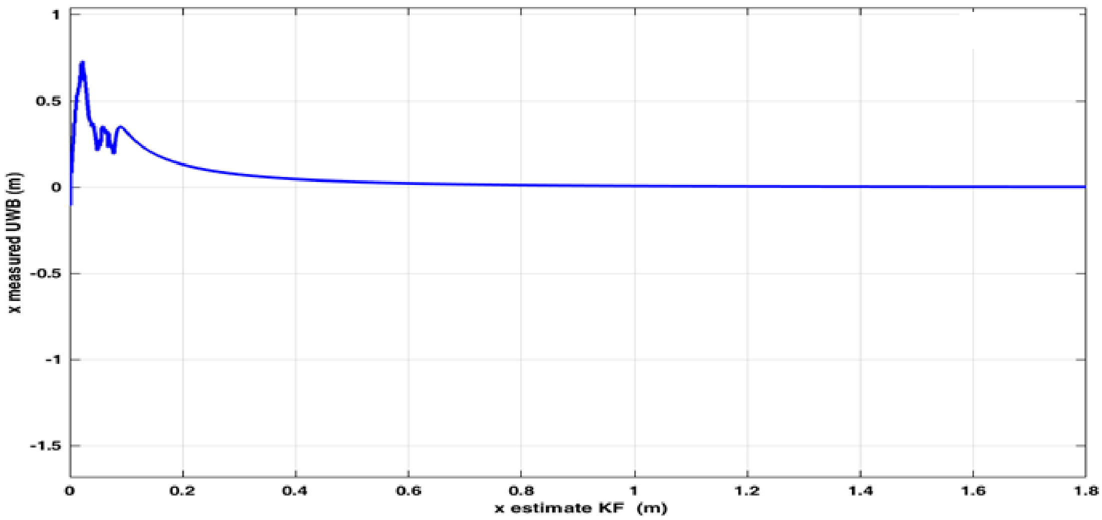


Figure 6 Relation between the actual and estimated values

3.1 Limitation of Kalman Filter Algorithm

In this study, various design methods for Kalman filters with uncertainties were examined. Furthermore, three cases. were observed where Kalman filters exhibit limitations in their performance.

Table 2 Kalman filter cases

Poor Observability	In cases where the process is poorly observable, it is recommended to consider changing the sensors or adding new sensors to improve the observability of the system.
Numerical Instability	An important observation is that in certain situations, the covariance matrices used in the Kalman filter may become asymmetric, which can potentially lead to divergence in the recursive computation.
Blind Spot	It is observed, when the process noise and measurement noise covariance matrices are considered to be very small, the state estimation error-covariance rapidly decreases.

3.2 Advantage of Kalman filter

The Kalman filter is commonly used in a wide range of applications, such as aerospace, control systems, and robotics[30][31][32]. However, such explanations tend to overlook the fact that there are some advantages to using a Kalman filter, as shown in Table 3:

Table 3 Advantage of Kalman filter

Optimal Estimation	The Kalman filter algorithm strives to provide the best possible estimate of the system's state based on the available data.
Dynamic Estimation	The suitability of the Kalman filter for real-time applications is indeed one of its significant advantages.
Handles Noise	One of the strengths of the Kalman filter is its ability to handle measurement errors and uncertainties effectively.
Real-Time Tracking:	The Kalman filter is well-suited for applications that require continuous monitoring and tracking of the system's state.
Adaptable	Can be used to estimate both linear and nonlinear systems.
Efficient	The Kalman filter is known for its computational efficiency, making it suitable for applications where computational resources are limited.
Versatility:	The Kalman filter has found wide applications in various industries, including robotics, autonomous vehicles, aerospace, and many others.

To conclude, the Kalman filter is a powerful and versatile tool for state estimation and prediction in the presence of noise and uncertainty. It assists in providing a robust framework for the combining measurements of a system's state and predicting it accurately and efficiently.

4. Conclusion

The Kalman filter is comprehensively applied in the numerous fields, for example engineering, robotics, and finance, for guessing and forecasting the state of systems that include unclear or noisy measurements. In this study, the data gained from sensors is handled using the Kalman filter to make forecasts and rectify any mistakes in the sensor readings. The aim of this research is to enhance the localization method of a mobile robot via the execution of the Kalman filter. By integrating the Kalman filter into the localization system, the precision and consistency of the robot's position can be improved. The outcomes of using the Kalman Filter for localization in the mobile robots advise that their execution significantly develops the precision of situation guesses in the noise and uncertainty in the sensor readings. Researchers have exposed that using the Kalman filter in simulation situations like Simulink enhances navigation performance for mobile robots, mainly in complex environments. The technology efficiently incorporates data from the numerous sensors, offering a methodical technique for the robot localization error reduction and real-time correction. In addition, the Kalman filter enhances localization precision and improves more reliable autonomous mobile robots capable of steering in challenging situations. Future work will look into further refinements of filter parameters and examine other filtering approaches to enhance the localization performance more.

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