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Optimization of improved extended Kalman filter for mobile robot Navigation

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Abstract: The Kalman filter is widely used in different applications, such as signal processing, modem control, and communication. It is instrumental in estimating system states with unknown statistics. The application can be significant in improving the accuracy and precision of state estimation for both linear and non-linear systems. The Extended Kalman Filter (EKF) is one of the important methods for the non-linear application of the Kalman filter, among other variations. The resulting expressions exhibit unity in that they apply to different situations involving localization procedures. This work presents the optimization of an improved EKF for mobile robot navigation by finding the best ways to reduce the time taken to complete the job.
Keywords: *Extended Kalman filter EKF, Kalman filter, Nonlinear, Optimization.*

1. Introduction

In recent decades, the localization problem has been extensively studied, and many approaches have been developed to estimate robots' status [1].

Mobile robots are widely used in many fields, including construction, entertainment, medical care, planetary exploration, warehouses, agriculture, industrial automation, and product deliveries [2]. Several research is being conducted in mobile robotics to improve navigation in challenging and complex environments [3].

A mobile robot can independently move and complete tasks. It achieves this with perceptual and control systems or cognition units coordinating all its subsystems that comprise the task [4]. The Kalman Filter (KF) can safely integrate visual annotations for navigational purposes with additional information from the sensor and inertial sensors [5, 6]. The KF primarily relies on an iterative approach that utilizes store or historical data on noise characteristics to adjust accordingly and filter the noise. The KF is better and suitable for linear stochastic processes. Conversely, the Extended Kalman Filter (EKF) can be applied to non-linear processes. Regarding both noise estimating and process designs, the EKF algorithm can be widely applied in a non-linear system with autonomous noise. Since most systems in engineering are non-linear, the EKF is given more attention compared with KF [7]. However, there are two major issues with the EKF. Finding the estimate noise covariance matrix and the process noise covariance matrix is challenging for the EKF due to its difficulty obtaining previous information about the field of operation. If the EKF obtains the fixed noise covariance matrices and the prior information of the operation field, it is difficult to fit all of them [7].

For issues involving state estimation, the Extended Kalman Filter (EKF) has been a long attractive method. when connected equations have directed the system's dynamics for the past sixty years [2]. Though the traditional demonstration of EKF is provided in the global coordinate, numerous studies have modified the Kalman filter approach to accommodate systems that exist on smooth manifolds. It is

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possible to use the traditional extended Kalman filter with any choice of local coordinates, which gives better benefit for filter operation by reducing linearization error [8].

The aim of this work is enhancement of mobile robot navigation for non-liner motion by using the improved EKF. The rest of this paper as follows: In Section 2, related work presents the relevant literature review. Section 3 presents KF. Section 4 presents the Extended Kalman filter configuration. Section 5 presents the EKF performance. Section 6 presents the comparison between linear and nonlinear navigation. Formulation is presented in Section 7. Finally, the article's conclusion presents in Section 8.

2. Related Work

The Kalman filter is an effective recursive computational filter that utilizes noisy measurements to determine a system's internal state. It is essentially used for linear systems, while its basic formulation is only appropriate for linear systems [9]. KF derivatives deal with the first branch of the approaches that apply filters [10, 11]. The Kalman filter, known for its reliability, combines the sensory data input and estimates the robot's state [12]. The Kalman filter is regarded as the best estimation for uncertain systems [13].

While the Kalman filter (KF) assumes that Gaussian noises affected the data, mostly in practical situations. KFs are primarily designed to handle linear system problems in their most basic form [14]. However, KF is now used in various contexts, mainly autonomous robot navigation. It is a system of mathematical formulas that provides a practical and effective computational format for estimating a process's state to minimize the mean error [15]. KF is essential in several aspects, including its estimated, current, and prospective states. Researchers have demonstrated several navigation-related Kalman filter applications, including integrated navigation systems [16] and inertial navigation [17].

Navigation focuses on tracking and managing a mobile robot's movements [9, 18]. Mobile robot navigation techniques can increase the accuracy of state estimates for a linear or non-linear system. Accurate localization information is necessary for autonomous mobile robots to navigate in any environment [15, 19, 20].

The Kalman filter (KF) approach is a robust mathematical technique commonly used to tackle estimation problems. RE Kalman devised this technique in 1960. The KF approach combines a series of equations that provide a recursive solution to discrete difficulties. The best example of this approach's output is the efficient estimation of past and future positions; mobile robots' positions and locations (x, y, and u) are the best examples. Because of its benefits of being more practical and straightforward, the Kalman Filter (KF) has emerged as one of the most popular estimation approaches used in estimating states [21, 22].

KF is a type of Bayes filter that uses the Gaussians to represent posteriors [23] for example, the distributions of unimodal multivariate that can be effectively represented by reduce some parameters that used in the process. The two nonlinear techniques that are most frequently employed in practical engineering are the unscented Kalman filter (UKF) and the Extended Kalman Filter(EKF) [24-26].

The Extended Kalman Filter (EKF) considers the most popular used and the most well-known. It is frequently utilized the algorithm that applies the first-order Taylor series approximation to the conventional linear recursive Kalman filter algorithm [9]. Several algorithms are being developed for coordinate position estimation using the Extended Kalman Filter (EKF) [27]. The EKF uses the Taylor expansion up to the first order to repress the higher orders and only deals with the linearized errors [28, 29].

3. Extended Kalman Filter (EKF)

EKF is considered the widely used approach for estimating in various applications. It is an improved variant of KF. The Kalman filter (KF) is the ideal and best choice when the system under consideration is linear and Gaussian random variables represent the uncertainties [30]. As a linearized system, the EKF used to deny the nonlinear terms of its related noise [31, 32].

The Extended Kalman filter (EKF) is a powerful navigation filter that is adept to handle linearized errors and restrain higher orders. EKF should be used in nonlinear systems due to its dependence on the first-order Taylor expansion. In dynamical systems, the Extended Kalman Filter (EKF) is an estimating approach widely utilized in many domains involving the state estimation using physical sensor readings [24, 26, 33].

The EKF is most effective state estimation approaches, It is frequently used to estimate the system state variables and measurement noise when some state information is available [34]. Since the Kalman filter can minimize the estimated mean square error variance, it is a popular choice for solving nonlinear systems' state variable estimation problems. Several engineering fields, including aerospace, marine navigation, control systems, manufacturing, and many more, have effectively used linearized EKF [35]. The KF is useful for engineering applications and also for time series analysis. In order to improve localization, two distinct distributed and centralized architectures based on the Extended Kalman Filter (EKF) data fusion method using integrating multi-sensor data [35-37]. The two main approaches to implementing the EKF are the error state space formulation (indirect formulation) and the total state space formulation (direct formulation). Conversely, error state space measurement formulation is nearly independent of vehicle motions and consists solely of system error.

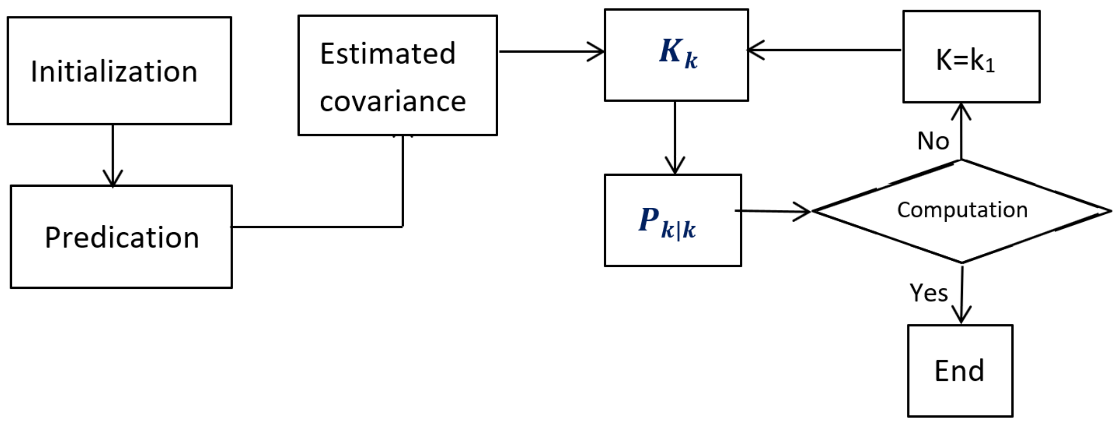

Figure 1.
Extended Kalman Filter Computation.

4. Extended Kalman Filter Configuration

When dealing with sequential localization issues in mobile robots, the extended kalman filter has shown to be a popular and standard solution [38]. It solves the estimate problem for a nonlinear model [39]. The primary principle behind the Extended Kalman Filter (EKF) configuration for error state estimation is to re-linearize each estimate as soon as it is obtained. A best reference state of the trajectory is included in the estimation process when it is a new state estimate is created.

The change of the nominal path to the estimated path is an easy and efficient way to solve the deviation problem. The Extended Kalman Filter has some similarity to the linearized Kalman filter, except that the linearization occurs around the filter's estimated trajectory rather than a precomputed nominal trajectory. The Extended Kalman Filter is comparable to a linearized Kalman filter. The only adjustment needed is substituting x^k for x nom k when evaluating partial derivatives.

In other words, since the filter's estimates are based on measurements, the partial derivatives are assessed along an updated trajectory. As a result, the filter gain sequence depends on the sample measurement sequence. The linearization assumption is valid if the problem is sufficiently observable, as shown by the covariance of the estimation uncertainty. This is because the differences between both estimated trajectory and actual trajectory along which the expansion is made will remain minimal. EKF implementation has two configurations, such as the error state estimate vs. total state estimate [13].

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The EKF implementation's configuration has an incorrect state estimation, as shown in Fig. The EKF equations are summarized in the table using an error-state formulation.

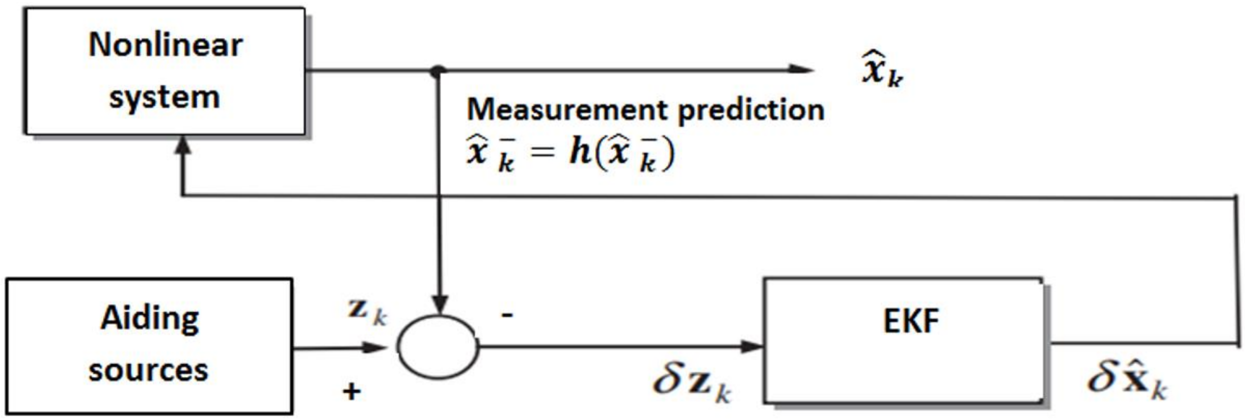

Figure 2.
Extended Kalman filter configuration with error state of estimation.

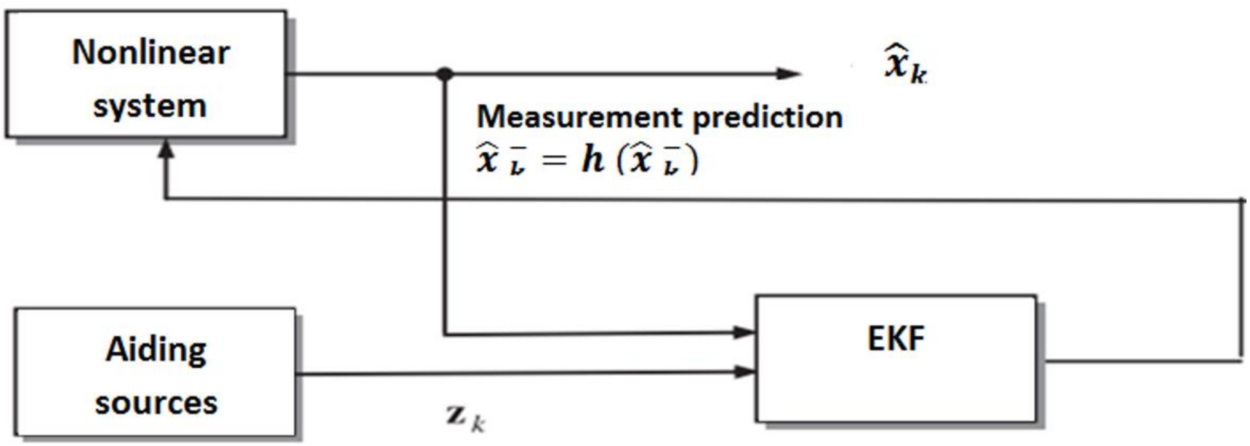

Figure 3.
Extended Kalman filter configuration with total state of estimation.

With the total-state of estimation, the configuration of the extended Kalman filter, it is possible to track the overall estimations rather than the incremental ones using the fundamental state variables. The EKF's basic linearized measurement equation expresses that the measurement given to the Kalman filter when working with incremental state variables is $z_x\ h\ \delta\ \check{x}_k\ ;k$ rather than the entire measurement (nonlinear) z_k. The equation for the incremental estimate can be updated at step k.

5. Extended Kalman Filter Performance

Using a mathematical model to depict the system is essential when employing an EKF. I This means the designer for EKFs must understand the system sufficiently to explain its behavior. EKF is a challenging type of implementing a Kalman filter. Accurate modeling of the system noise is another difficulty for Kalman filter. The functions of the preceding anticipated states are estimated when non-linear functions are present.

The covariance of the linear system in the EKF approach is obtained analytically by determining the posterior covariance matrices following the linearization of the dynamic equations. The state distribution for the EKF is estimated by computing a generalized reduced value (GRV). In this case, the

EKF provides "first-order" approximations to the optimal terms, such as gain and prediction. Thus, much consideration is given to how these models operate when localized. So, applying linear KF and EKF could improve the navigation process [14].

6. Comparison Between Linear and Nonlinear Navigation

Table 1 shows the comparison between linear and nonlinear navigation with several factors.

Table 1.
Comparison between linear and nonlinear navigation.

Type / Factors	Linear navigation KF[40]	Nonlinear navigation EKF[41].
Power system	The Kalman filter (KF) is a potent instrument for estimating its current state. advanced versions of the filters—which are mostly designed for linear filters—are constantly required. When it comes to power system applications, the efficacy of Kalman filtering approach in enhancing the computing performance of the conventional steady-state estimate method is undeniable. This is particularly true when a linear dynamic system is under the control of non-linear functions [42]. One typical way to build a recursive of the state estimation system is by using Kalman Filter (KF) which have numerous variations [19]. These systems use a kinematic model of the system and the measurement variance with the inputs to estimate an updated state [42, 43].	When it comes to the fluctuations, the extended Kalman filter consider as nonlinear type that used to estimate the process and all the determination related to its process that be linearized [19].
Use	The actual systems assist as models for each of these estimators. This non-linear filter linearizes concerning the covariance and mean at present.	For GPS and the estimation for nonlinear systems, the EKF may consider as the standard type.
Application	Kalman filtering, a crucial tool, is widely used for state estimation and forecasting system applications in the weather, stock market, and other industries.	EKF might not relish the status of being the standard filter [44].
Effective	KF quickly and effectively solves the challenge of processing noisy data with errors and imperfections.	The Extended Kalman Filter (EKF) provides first- and higher-order linearization approximations for nonlinear systems [14, 45].
Error	For real-time estimates, KF is useful because it is quick and takes little memory. It simply needs to store the history of the prior state [45, 46].	The EKF is a suitable option in cases where the measurement error values are precisely resilient, especially when measurements are prone to significant errors [15].
Determination	Identifying and differentiating arbitrary signals [15].	The EKF's position determination accuracy is a critical factor, always needing to be higher than the GLSA or GRA accuracy [47, 48].
Capacity	The capacity of linear Kalman filtering to handle partially deterministic data when process noise is absent.	Based on linearization, the extended Kalman filter (EKF) extends the KF to the nonlinear case. The highly "linear" form is unsuitable when considering singular covariance matrices and nonlinear dynamics [48].

7. Formulation

In the EKF, the observation state space model and state transition model may contain many non-linear functions rather than linear functions of the state.

$$x_k = f(x_{k-1}, u_{k-1}) + w_{k-1}$$
$$z_k = h(x_k) + v_k$$

The process noises, denoted by w_k and the observation noise by v_k , zero mean multivariate Gaussian noises with covariance are Q_k and R_k, respectively. Additionally, the expected state is used to compute the predicted measurement, and the functions f and h assist in estimating the anticipated state by utilizing the prior estimate. However, f and h cannot be applied straight to the covariance. Thus, the computation of a matrix of partial derivatives, or the Jacobian, is necessary. The Jacobian is computed at each time step using the current expected states as guidance. These matrices are employed in the KF equations. In actuality, the non-linear function around the current estimate is linearized by this method.

7.1. The Predict and the Update Equations

1- The Predicted State $\check{x}_{k(k-1)} = f(\check{x}_{h-1/k-1.u_{k-1}})$

a- The predicted estimate of covariance $P_{k|k-1} = F_{k-1}P_{k-1|k-1}F_{k-1} + Q_{k-1}$

b- The innovation or the measurement residual $\check{x}_k = (z_k - h(\check{x}_{k|k-1})$

c- The innovation (or the residual) covariance $S_k = H_k\, P_{k|k-1}\, H_K^T + R_k$

d- The optimal the Kalman gain $K_k = P_{k|k-1}\, H_K^T\, S_K^{-1}$

2- The Update Step

a- The updated state of the estimation $\check{x}_{k|k} = \check{x}_{k|k-1} + K_k\check{y}_k$

b- The updated estimation covariance $P_{k|k} = (1 - K_kH_k)P_{k|k-1}$

Where the following Jacobians are defined as the state transition and the observation matrices.

$$K_{k-1} = \frac{\partial f}{\partial x}|_{\check{x}_{k-1|k-1}}, U_{k-1}$$

$$H_k = \frac{\partial h}{\partial x}|_{\check{x}_{k|k-|}}$$

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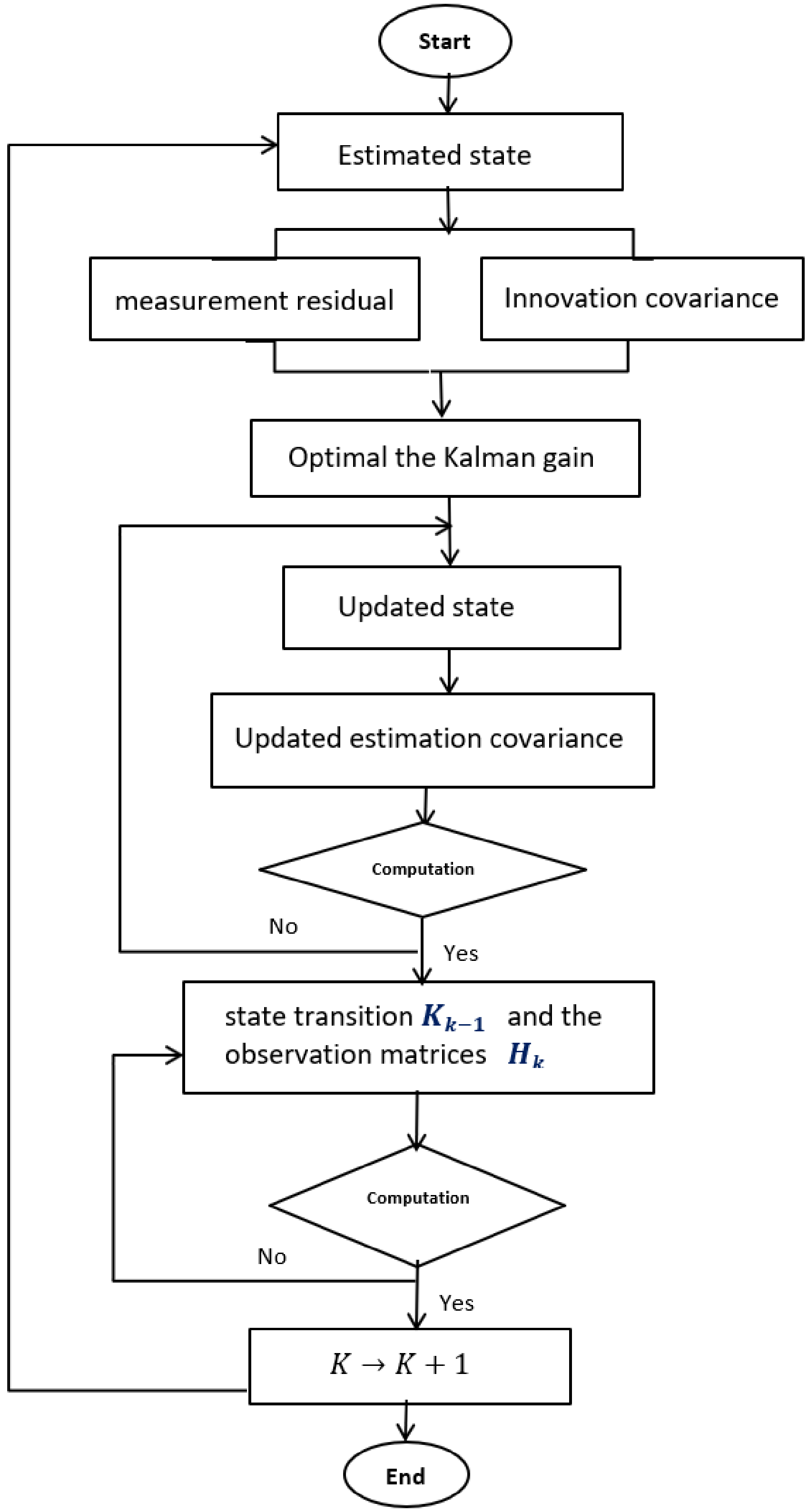

Figure 4.
Flow chart of improved EKF.

Table 2.
Enhancement of use Extended Kalman Filter.

Factors	EKF
Accurate	More accurate than other localization approaches. The EKF maintains the recursive update version of the Kalman filter, which is computationally effective [19].
Estimation	An improvement in prediction error estimation and the estimated noise covariance matrix.
Suggested algorithm	By modifying an array's geometry, the suggested algorithm's accuracy could be further increased.
Use	The extended Kalman filter is a valuable tool when dealing with nonlinear systems.

Table 2 shows the enhancement of EKF in different factors where EKF is more accurate compared with other navigation processes.

8. Conclusion

EKF is a good solution for issues involving estimation process. This paper presents an improved navigation method according to the Extended Kalman filter which enhances the navigation process. This work aims to investigate a mobile robot localization method that uses the EKF to determine an accurate mobile robot location. The resulting expressions exhibit unity in that they apply to different situations involving investigating localization procedures. The combined observation can approximately eliminate measurement errors and improve the accuracy of cooperative navigation.

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