# A survey on Kalman Filtering for Unmanned Aerial Vehicles: Recent Trends, Applications, and Challenges

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# A survey on Kalman Filtering for Unmanned Aerial Vehicles: Recent Trends, Applications, and Challenges

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*Abstract*— **This study presents recent trends, challenges, applications, and design methodologies of Kalman filter which becomes a cornerstone for the application of unmanned systems. The elaborated filters are range from Kalman to its improved modifications. The algorithms are also widely used in control theory and this aspect of the study makes it a beneficial guide to a large number of readers. Furthermore, the inertial measurement unit, which is the core for the unmanned vehicles, can be designed with different filtering strategies. The filters are compared via a number of features.**

***Keywords—Kalman filters, state estimation, inertial measurement unit, fault-detection, unmanned systems.***

## I. INTRODUCTION

The theoretical and practical improvements of information systems include hardware and software have been essential in the development of unmanned systems [1]. Among them, unmanned aerial vehicles (UAVs) have attracted a great deal of attention in the control-engineering framework. A number of advantages have been reported for protecting human life in various missions. To mention a few, UAVs can be useful for many dangerous environments. With this motivation in mind, the potential of UAVs has been increasing day by day in various application areas.

From a safe operating point of view, an unmanned vehicle has to provide all the necessary conditions for reliability, safety, and security. However, the blending of overall imperfections with real environments, measurements, control algorithms, and communication constraints, makes the physics of the problem very complicated.

There are a number of critical steps that must be conducted in the development of UAVs. The fundamental steps can be listed as system identification, sensor fusion, filtering issues, deployment of communication infrastructure, and controller design.

Kalman Filter, which is an estimation algorithm in linear state-space models, has a very important place in linear filter theory [1]. Kalman filter is a recursive estimation filter, which is able to estimate the current state from the last previously estimated state and new measurement.

The main motivation of this research is the necessity of evaluating Kalman Filter applications for UAVs to express their advantages and drawbacks. Kalman Filter, which is mostly used in many fields along with aviation applications, can produce optimized predictions for the next states according to the previous states of the system. It differs in this from the algorithms of type "batch", because it does not keep any history of measurements or estimates.

In this study, the applications of Kalman filter and its modifications, which have been devoted to several missions of UAV design and control, are investigated.

There are two fundamental problems encountered in practice regarding the mathematical modelling of the systems. The model cannot represent the real system exactly due to the uncertainties. The measurements from the sensors are not perfect. Kalman Filter processes the data obtained by using measurement dynamics, noise in the data and initial values of the system and performs state estimates of the system with minimum error.

Numerous examples have been reported on the application of Kalman filtering for various tasks in unmanned ground/aerial vehicles navigation [2], motion planning, trajectory estimation and optimization [3], target tracking, guidance and control [4], fault estimation, attitude determination, state estimation [5], and other tasks in the industry [6].

The contributions of this study are given as follows: Various filtering methods used in the design of the inertial measurement unit, which is the core of unmanned aerial vehicles applications, are examined. In addition, general information about the Kalman filter as well as its improvements are given and performance comparisons are presented for each type of Kalman filter. The application examples of Kalman Filter in linear or non-linear systems are detailed with their advantages and drawbacks. From this aspect, the present research provides a practical guide of Kalman filters for unmanned aerial vehicles.

This paper is organized as follows. The theoretical background of Kalman filter is given in Section II, Improvements on Kalman filter is given in Section III. Kalman filter applications for unmanned aerial vehicles are given in Section IV. Finally, the concluding remarks are addressed in the last section.

## II. THEORITICAL BACKGROUND OF KALMAN FILTER (KF)

In standard Kalman filter, which is derived from the least-squares method, it is aimed to combine mathematics and the physical world. In control theory, Kalman filter is known as a linear-quadratic estimator (LQE) that uses a series of measurements, including statistical noise and other errors.

This section investigates the central notion of the Kalman filter. The scheme of data-driven modelling is depicted in Figure 1.

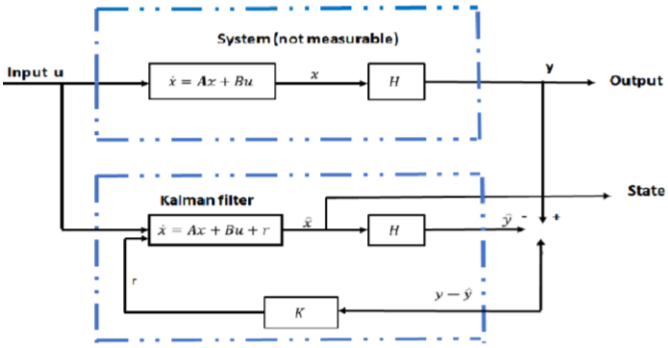


Fig.1. The structure of Kalman Filter

The algorithm takes place in two phases: the first one is the predictive phase, which the filter retrieves the last value of the estimated state to estimate the state at the current instant. The second one is the update phase, wherein a new measured value is introduced, allowing to correct the estimation of the first phase, and thus obtain a more precise a state.

The process model describes the change in state from time *k-1* to time *k* as follows [7]:

$$x_k = F\, x_{k-1} + B\, u_{k-1} + \; w_{k-1} \tag{1}$$

The state transition matrix is defined as *F*, the control input matrix is defined as *B*, previous state vector is defined as $x_{k-1}$, control vector is defined as $u_{k-1,}$ process noise vector that is assumed to be zero-mean Gaussian with the covariance Q is defined as $w_{k-1}$.

A measurement model should be obtained that describes the relationship between state and measurement in the current time step *k*. This model can be defined as:

$$z_k = Hx_k + \; v_k \tag{2}$$

The measurement vector is defined as $z_k$**,** the measurement matrix is defined as *H*, $v_k$ is the measurement noise vector.

Prediction and update are the two structures that compose the algorithm of the Kalman filter [7]. There are two equation in prediction part. The flat operator, "^", is used to mean an estimate of a variable. Superscripts "-" and "+" are used to mean predicted and updated estimates. First one is $\hat{x}_k^-$ which is called as predicted state estimate. Second is $P_k^-$ which is called as predicted error covariance.

$$\hat{x}_k^- = F\, \hat{x}_{k-1}^+ + B\, u_{k-1} \tag{3}$$

$$P_k^- = FP_{k-1}^+F^T + Q \tag{4}$$

There are four equation in update part.

$$\dot{\hat{y}}_k = z_k - H\, \hat{x}_k^- \tag{5}$$

Measurement residual $\dot{\hat{y}}_k$ is the difference between the true measurement $z_k$, and the estimated measurement $H\, \hat{x}_k^-$. Calculating Kalman gain $K_k$ is a very important process, because it plays an important role in calculation of update state estimation " $\hat{x}_k^+$".

$$K_k = P_k^- \; H^T \; [R + HP_k^- \; H^T]^{-1} \tag{6}$$

$$\hat{x}_k^+ = \; \hat{x}_k^- + K_k \dot{\hat{y}}_k \tag{7}$$

$$P_k^+ = (\mathrm{I} - K_k H)\, P_k^- \tag{8}$$

It is important that the updated error covariance "$P_k^+$" is smaller than the predicted error covariance. This means that the filter is more accurate than the state estimate after it is used in the measurement update phase.

## III. Improvements on Kalman Filter (KF)

In real-time applications, many different factors reducing the performance of the Kalman filter have been reported. To mention a few, model errors, as well as model uncertainties unavoidably degrade the performance of Kalman filter. Furthermore, a number of enhancements are required for the Kalman filter to be applied to nonlinear systems. Thus, various improvements have been investigated on the application of Kalman Filter such as Extended Kalman Filter (EKF), Unscented Kalman Filter (UKS), Robuts Kalman Filter (RKF), Adaptive Kalman filter (AKF).

### *A. Extended Kalman Filter (EKF)*

The extended Kalman filter is one such example for these enhancements. EKF is a filter created by replacing the traditional Kalman filter, especially for the application of system or measurement models in non-linear situations. The EKF is a filter that considers continuous-time dynamic systems and discrete-time measurements for nonlinear system estimation through linearization. EKF uses linearization process ignoring high-order terms in the Taylor series and requiring Jacobian matrix calculation [2, 4].

$$\dot{x} = f\,(x,u,t) + D(t)w \tag{9}$$

$$z_k = y\; [\; x(t_k), k\; ] + \; v_k \tag{10}$$

where a system model is defined as *f*(*x*,*u*,*t*) and a measurement model is defined as *y*(*x*,*k*). Further, *w* and $v_k$ are the process and measurement noises, respectively.

$$w \approx (0,Q) \;\;,\;\; v_k \approx (0,R)$$

The first step in prediction is to predict the next state of the system input *u*.

$$\dot{\hat{x}} = f(\,\hat{x}\,, u, t\,) \tag{11}$$

$$\dot{P} = F(\,\hat{x}\,,\, t\,)P + PF^T\;(\,\hat{x}\,,\, t\,) + DQD^T \tag{12}$$

$f(\,\hat{x}, u, t)$ and *P* can be obtained from prior measurement update and the measurement estimate is updated as follows [4]:

$$K_k = P^-\,(\,t_k)\; Y^T(\,\hat{x}_k^-)[Y\;(\,\hat{x}_k^-)\; P^-(\,t_k)\; Y^T\;(\,\hat{x}_k^-)\; + R\,]^{-1} \tag{13}$$

$$P(t_k) = [\; I \text{ - } K_k\; Y(\,\hat{x}_k^-)\mathrm{P}^-(t_k) \tag{14}$$

$$\hat{x}_k = \; \hat{x}_k^- + K_k[\; z_k \text{ - } Y(\,\hat{x}_k^-\,, k)] \tag{15}$$

*F*(*x*,*t*) and *Y*(*x*) are Jacobians derived from $f(\,\hat{x}, u, t)$ and *y*(x, *k*) [4].

$$F(\,x,\,t\,) = \frac{\partial \mathrm{f}(\,x{,}u{,}t)}{\partial x}\;,\;\; Y\,(\mathrm{x}) = \frac{\partial \mathrm{y}(\,x{,}k)}{\partial x} \tag{16}$$

### *B. Unscented Kalman Filter (UKF)*

In Extended Kalman Filter, linearization is performed using Jacobian matrix and calculations of Jacobian matrix increase the cost. Moreover, when estimating in high-order nonlinear systems in Extended Kalman Filter, it is difficult to obtain correct results because due to the linearization. In order to reduce these disadvantages, EKF-based Unscented Kalman Filter (UKF) was developed [1] .

UKF captures mean and covariance estimates with a deterministic sampling approach [8]. Thus, the Unscented Kalman Filter (UKF) is easy to implement. Furthermore, UKF provides more robust forecast performance.

### *C. Robust Kalman Filters (RKF)*

The Robust Kalman filter can be applied in uncertain discrete time systems. It provides an upper-bound to the variance of the filtering error to resolve parameter uncertainties in the RCF state and output matrices [8, 9]. A robust Kalman filter (RKF) processing data under measured sounds has been applied to the FPID control strategy. Thus, the robustness and anti-interference feature of the UAV system is increased and the effect of outliers on the updated parameters is minimized [22]

### *D. Adaptive Kalman Filter( AKF)*

In the traditional Kalman filter, an accurate system model and stochastic information are required for predictions to be correct. However, it is very difficult to obtain almost 100% system information in real applications. Adaptive Kalman Filter (AKF) proposed to reduce the impact of this deficiency. AKF overcomes errors in the prediction of nonlinear state space models that may result from incomplete system information.

## IV. Kalman Filter Applications for Unmanned Aerial Vehicles

This section presents the applications of the Kalman Filters for UAV applications. The elaborated filters are applied for several tasks such as system identification, sensor fusion, state estimation, control, fault detection, as well as fault tolerant control. The application of Kalman filters UAVs are tabulated in Table I.

Table 1: Kalman Filter Applications for UAVs

| Applications | KF | EKF | UKF | RKF | AKF |
|---|---|---|---|---|---|
| System Identification | [12], [13] | [14],[15], [16], [17] | [18], [19] | | [20] |
| Sensor Fusion | [21] | [22] | [23] | [10] | |
| State Estimation Control Design | [24], [25] | [4], [5], [17],[26] | [27], [28] | | [29] |
| Fault-Detection, Fault-Tolerant Control | [30] | [31], [32] | [33] | [34] | [35], [36] |

### *A. Kalman Filters for Identification of UAV*

System identification, which can be used to characterize different components in unmanned systems or to construct the mathematical model of the system with measured input-output data [37], is an important step in designing the controllers of UAVs. In addition, a discrete model for predictive control of UAVs can be obtained by system identification. The obtained models can be used as a prediction system in controllers.

The reports on the Kalman filtering devoted to system identification can be summarized as follows: Kim Y. et al. proposed two filters to make parameter estimates. Kalman filter (KF) for linear dynamics and Unscented Kalman Filter UKF for nonlinear dynamics are proposed[13].

It is to be noted that UAVs have a multi-input-multiple output structure. Thus, data from sensors on UAVs are mostly non-linear and time-varying values. This makes it tedious to estimate the parameters and determine the system model. For nonlinear systems, the classical Kalman filters are evaluated to be inadequate. An EKF has been proposed to define system dynamics in [16]. It is to be noted that EKF, which uses an iterative nonlinear filtering approach, can be applied separately for linear and non-linear models in the identification of UAVs.

A further example of EKF has been proposed for both state and parameter estimation of a UAV [17]. EKF is proposed to deal with nonlinear effects in [14], wherein, determination of the stability and control parameters of the nonlinear unmanned aerial vehicle model is investigated. While making these definitions, the dynamic effects of some external factors occur. Furthermore, Munguía R. et al. propose an improved EKF that estimates the model parameters of the UAV using measurements directly obtained from sensors on multi-rotor UAVs. With these observations, EKF, which updates with the measurements taken from the sensors, can be able to predict all model parameters of multi-rotor aerial vehicles [15].

Information obtained from many sensors can be used during the design of controllers. However, a number of problems are encountered in cases such as noisy measurements as well as the nonlinearity of the data received from the sensors. Some filters are recommended to tolerate these problems. In this article, UKF and EKF performances have been examined and compared for parameter estimation [18]. UAVs are highly complex systems with multi inputs. Thus to construct an exact mathematical model is a challenging issue. However, a UKF is highlighted to estimate the model of the UAV through the flight data [19].

Chiella et al. define the mathematical equivalent model to protect the lithium-ion batteries in UAVs. Further, the parameters used to predict the next charge rate of the battery are estimated. Toward this goal, an adaptive kalman filtering (AKF) is addressed [20].

### *B. Kalman Filters for Sensor Fusion of UAV*

Sensor fusion and the filtering of measurements are one of the most important points for unmanned vehicles. The investigation of sensor fusion techniques has been very attractive. For these purposes, Kalman filter is a powerful tool for sensor fusion applications with its recursive nature. With this motivation in mind, this section presents filtering issues dedicated to sensor fusion of UAVs.

The performance of the estimation strategies is elaborated with a number of examples. For instance, Arreola L. et. al. propose a position estimation strategy which is based on low-cost devices and optical flow algorithm. Towards this goal, an extended Kalman filter algorithm is employed [21]. A location estimation system using low-cost devices for UAVs has been proposed in [21], wherein the information from GPS and inertial navigation sensors (INS) are used to estimate the position of the UAV. GPS and INS information is fused in the Kalman Filter. In addition, EKF is presented to estimate the position using data obtained from the optical flow algorithm to improve the UAV position estimation [21]. A low-cos PX4Flow optical sensor, which is an open-source hardware and software platform comprising CMOS vision sensor, a gyroscope, and a sonar range finder, is addressed in [38].

Furthermore, a sensor fusion method, which is based on EKF algorithm, is addressed for estimating the velocity, position, and attitude of an UAV with a low-cost inertial measurement unit [22]. A number of experiments are conducted with various sampling intervals and loss data conditions to investigate the proposed algorithm.

An innovative fusion filter-based method is proposed by Yue L. et al to solve the problem of tracking quadrotors in the presence of interference and measurement noise. An example block diagram of a control structure of quadrotor is shown in Figure 2. Traditional PID cannot properly adjust its gain with environmental distortion. FPID has been proposed to reduce this disadvantage. In order to complement the shortcomings of FPID, the EKF and RKF are proposed. When the Kalman filter (KF) is applied to the system, the presence of outliers can seriously damage the compensation effect. If the necessary suppression measures are not taken, this abnormal value will greatly damage the monitoring performance of the system [10].

Another example of UKF based Kalman filter application is reported by Chiella et. al. [23], wherein a robust adaptive fusion algorithm is proposed for collecting data in an actual forest environment.

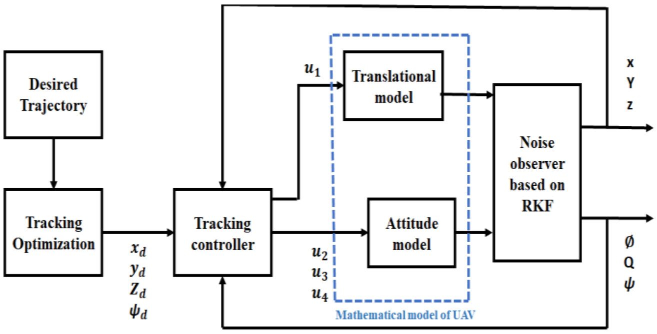


Fig.2. The control system of quadrotor [37]

### C. Kalman Filters for State Estimation and Control

The main purpose of using the Kalman filter is to be able to make state-estimation, rate estimation. This filter has increased the reliability of complex systems by reducing noise. Kwon H. et. al. address an EKF based Sliding mode control for attitude stabilization. The proposed algorithm estimates the attitude state by an EKF, then stabilizes the system with a variable structure control [4]. Song Q. et. al. address a control scheme that combines backstepping and PD controller for position and attitude control, respectively. Further, an unscented Kalman filter for both fast and slow modes estimates a wind-gust disturbance, which is to be considered as an external disturbance [27].

In a further study, an attitude estimation of a quadrotor type aerial vehicle is addressed through an observer that is based on Extended Kalman Filter [5]. The data losses are model as a random process.

Extended Kalman filter is employed separately for linear and non-linear models in the identification of unmanned aerial vehicles. The extended Kalman filter has been proposed for both UAV's state and parameter estimation [17]. The UKF has been recommended where EKF is inadequate to deal with some of the difficulties encountered in making the forecast of unmanned aerial vehicles [28]. Wang D. et al. propose a system to track the target and determine the states of the UAV in non-linear situations. To do this, a new AUKF system has been proposed by combining the UKF and AKF [29].

In yet another study, Zhang K. et al. investigate the flight control and tracking problem of a quadrotor with model uncertainties and external disturbances. A linear-quadratic regulation (LQR) tracking algorithm is addressed. However, several difficulties such as high nonlinearities, coupled dynamics, parameter variations, and uncertainties in the system dynamics, are encountered in LQR design [39]. To overcome these drawbacks, an Extended Kalman Filter (EKF) based LQR is proposed for online estimation of position, speed and engine dynamics using measured outputs. It is to be noted that more effective results can be obtained for disturbance rejection by the use of EKF [26]. The block diagram of the controller, which is designed based on LQR and EKF techniques, is shown in Figure 3.

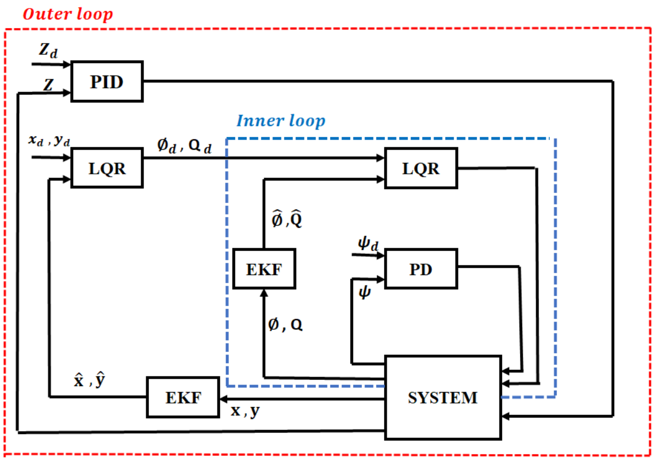


Fig. 3. The inner-outer control structure[26]

Hetenyi D. et. al. propose a method to check the position of the UAV [24]. However, the presence of noise brings a number of difficulties and makes the design of these control systems difficult. Thus, it is necessary to filter the signals from the sensors to create a stable and accurate measurement. With this motivation in mind, the Kalman filter is used to combine the sonar and accelerometer signals. In this algorithm, accelerometer data is combined with elevation data from sonar. As a result, it has been shown that the error generated by Kalman filter is relatively small and valid for correct altitude application [24].

### D. Kalman Filters for Fault-Detection and Fault-Tolerant Control of UAV

Fault detection, diagnostics, and fault-tolerant control are important in developing control algorithms, which can deal with failures occurring in critical tasks. A number of research studies can be summarized as follows: Egidio D'Amato, et. al. propose a fault-tolerant system for attitude estimation of UAV using low-cost magnetometers, accelerometers and gyroscopes. The Unscented Kalman Filter (UKF) has been used make to propose an approach to detection, isolation and reconstruction. It reduces the effect by identifying the error by comparing the predictions made by the UKF with the measured variables. The disadvantage of the filter is defined as the small delay in isolating the faults in the use of the UKF and the increase in the calculation cost. However, in the presence of a double fault, UKF guarantees a fail-safe behaviour [33].

It is important to determine the state of unmanned aerial vehicles correctly. However, some errors, noises, and distortions may be encountered in the state determinations. In these cases, it is necessary to detect the faults correctly, to eliminate their effects on the system and to prevent the deterioration of the system characteristics. RKF is suggested for realizing these situations in [34].

Ngo T. et al. address a method to control the vehicles in an unknown outdoor environment. To do this, the complementary filter and Kalman filter are designed to predict the exact state vector showing the movement of the body. Experimental results are presented to validate the design of these filters. The complementary filter takes gyro values as major factors and accelerometer values as minor factors. Therefore, the oscillation reflected in the angles of the accelerometer cannot affect the system much. It follows from this that the estimated angle of the complementary filter is more stable than the Kalman filter [25]. When buildings or trees block the UAV during flight, the GPS receiver cannot receive all satellite signals and generates an incorrect positioning signal that can be expressed as outliers present in the measurement noise. Therefore, it is very important to estimate the UAV's position.

It is known that faults, which have nonlinear nature, may cause fatal damages in unmanned systems. An AKF is proposed by Weimer F. et al. [36] to detect faults as well as to make correct definitions when different faults are encountered. In a further study, an actuator based sensor fault detection, as well as diagnosis algorithm, are presented in [30]. An actuator fault detection and diagnosis algorithm are proposed for a quadrotor type aerial robot in the presence of external disturbances [35]. The proposed strategy is based on adaptive augmented state Kalman filter. A neural network-based system has been proposed to detect malfunctions in unmanned aerial vehicles. This system is strengthened with EKF. It is also used to update the parameters in EKF Neural Network [31]. Liang Y. et al. propose EKF to detect the error in the UAV's navigation system and to obtain the correct values in the presence of any error [32].

## V. CONCLUSION

The practical improvements of UAVs have been increasing with the development of control system technologies, signal processing methods, and communication capabilities. However, the design, modelling, and control of UAVs bring a number of challenges due to the highly complex nonlinear nature.

The main goal of the current research is to explore Kalman filtering techniques devoted to system identification, sensor fusion, state estimation, fault detection, fault-tolerant control of UAVs. Furthermore, it is aimed to guide the control researchers on the filtering techniques during the modelling and control of critical systems. With this motivation in mind, recent studies on Kalman filtering for UAV applications are addressed.

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