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Article

Tracking Unmanned Aerial Vehicles Based on the Kalman Filter Considering Uncertainty and Error Aware

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Abstract: Recently, Unmanned Aerial Vehicles (UAVs) have made significant impacts on our daily lives with the advancement of technologies and their applications. Tracking UAVs have become more important because they not only provide location-based services, but are also faced with serious security threats and vulnerabilities. UAVs are smaller in nature, move with high speed, and operate in a low-altitude environment, which makes it conceivable to track UAVs using fixed or mobile radars. Kalman Filter (KF)-based methodologies are widely used for extracting valuable trajectory information from samples composed of noisy information. As UAVs' trajectories resemble uncertain behavior, the traditional KF-based methodologies have poor tracking accuracy. Recently, the Diffusion-Map-based KF (DMK) was introduced for modeling uncertainties in the environment without prior knowledge. However, the model has poor accuracy when operating in environments with higher noise. In order to achieve better tracking performance, this paper presents the Uncertainty and Error-Aware KF (UEAKF) for tracking UAVs. The UEAKF-based tracking method provides a good tradeoff among preceding estimate confidence and forthcoming measurement under dynamic environments; the resulting filter is robust and nonlinear in nature. The experimental results showed that the UEAKF-based UAV tracking model achieves much better Root Mean Square Error (RMSE) performance compared to the existing particle filter-based and DMK-based UAV tracking models.

Keywords: Kalman filter; non-parametric filtering; security; stochastic environment; tracking; unmanned aerial vehicle

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1. Introduction

As shown in Figure 1, UAV/drone communication can be divided into four main types: unmanned aircraft to unmanned aircraft (U2U), unmanned aircraft to ground station (U2Gs), unmanned aircraft to the network (U2N), and unmanned aircraft to satellite (U2S) [1,2]. With the advances in technology, cost-effective deployment, and tiny size, UAVs/drones have received wide attention due to their extensive use and potential threats. UAVs have been extensively used for different application purposes such as environment monitoring, agriculture, wildlife monitoring, disaster management, plant protection, photography, surveillance, and even by the military for warfare and delivery of product [3] (Figure 2). The wide spectrum of drone applications experiences several challenges, for instance, security, ownership, privacy, liability, safety, etc. [4–6]. Additionally, unmanned aerial vehicles pose significant threats if they are used for, e.g., drug trafficking, spying, carrying hazardous material for attacking, disturbing regular flight operations, and so on [7–9]. Thus, it is imperative to detect, localize, and track drones. Tracking drones is difficult compared to manned aircraft [10]; thus, police and government agencies are introducing new policies for detecting and tracking drones. Computer vision [11] and radar detection [12] are generally used for detecting drones. The significant growth of fifth-generation (5G) and Internet-of-Things (IoT) technology has led to increased usage of drones, bringing significant economic benefit for a wide range of civil applications [13]. Recently, several 5G-based drone localizations and tracking methodologies have been presented [14]; thus, researchers will continue to focus on the tracking of drones.

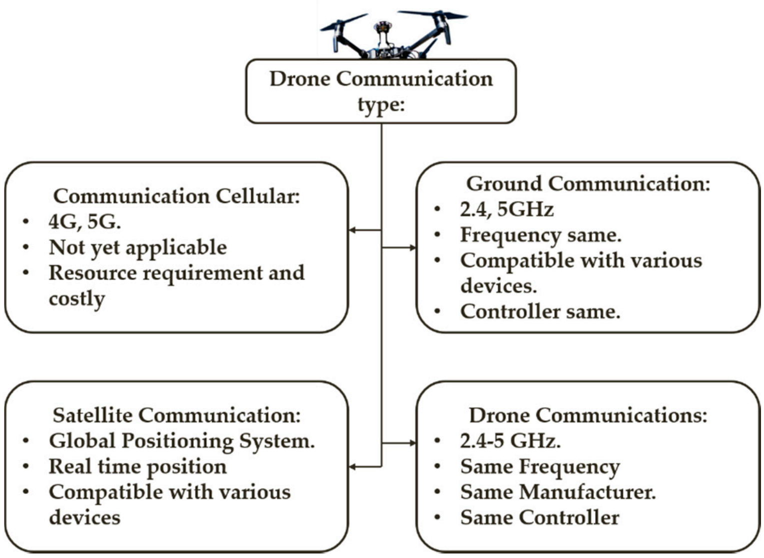

Figure 1. UAV/drone communication.

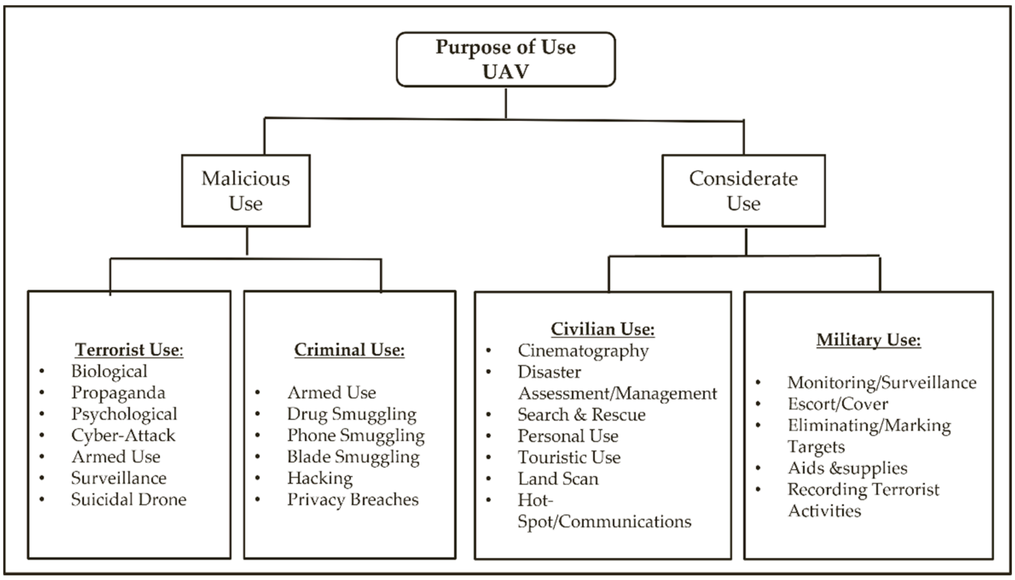

Figure 2. Purposes of UAV usage.

A UAV is a self-powered, radio-controlled, or autonomously flying unmanned aerial vehicle that can perform a variety of tasks and can be used multiple times. To realize the autonomous flight of UAVs and complete the designated tasks, their flight control, navigation, and guidance are the most critical technologies.

The basic task of the UAV automatic flight control system is to maintain the stability of the aircraft's altitude and track when the air interferes with the UAV, to change the aircraft's altitude and track according to the requirements of the ground wireless transmission instructions, and complete the navigation calculation, telemetry data transmission, task control, and management, etc. (Figure 3). The basic task of the UAV navigation system is to control the UAV to fly according to the scheduled mission route. The basic condition for realizing navigation is to be able to determine the real-time position and speed of the UAV's flight and other relevant parameter information. The basic task of the guidance system is to determine the relative position of the UAV and the target, control the UAV to fly, and, with a certain accuracy, guide the UAV to fly to the target along a predetermined trajectory [15].

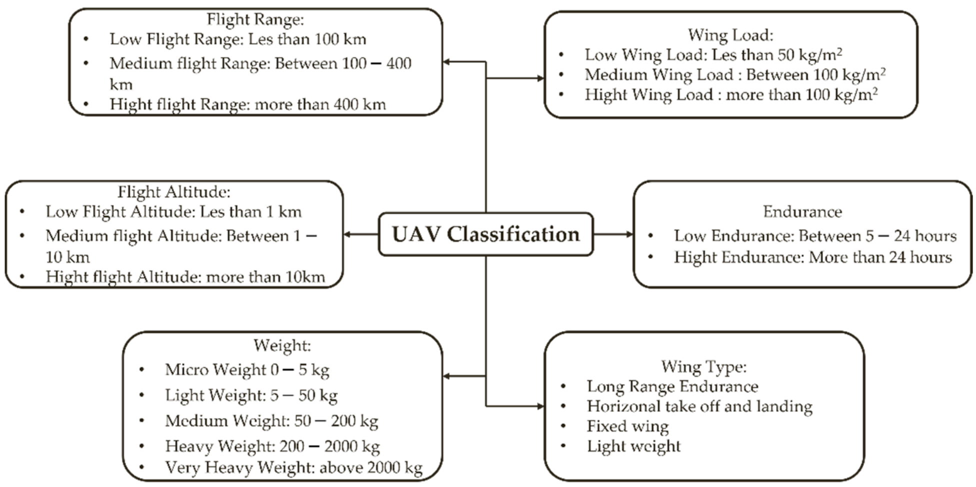

Figure 3. UAV classification.

Radar-based object detection mechanisms are a conventional application in radar communications. Generally, the radar is fixed in nature for detecting UAVs. With the advancement of technology, mobile radars are being used for detecting UAVs. These mobile radars can be shipborne, vehicleborne, airborne, or spaceborne. Modern UAVs can carry a load; thus, radars, such as Pule Doppler and Synthetic Aperture Radar (SAR), can be installed even in UAVs for tracking and intercepting other unidentified UAVs in a tracking environment. The number of existing methods [16–18] are aimed at only identifying drones, but the continuous tracking of drone trajectories was not considered. The operation of continuous tracking of drones is a state estimation problem. To address the state estimation problem in tracking drones' trajectories, the Kalman Filter (KF) is generally used [19]. In Ref. [20], the KF was employed for building an improved version of the Kalman filter for target tracking, namely, Unscented-KF (UKF). Similarly, Ref. [21] employed the KF for improving drone trajectory tracking, namely, Extended-KF (EKF). Both filtering methodologies use improved linearization methodologies of the KF for modeling nonlinear models into linearized state estimation problems. For modeling, random errors due to dynamic motions [22] converted measurement-KF and Unbiased Converted Measurement-KF (UCMKF) were presented [23,24]. Furthermore, for bounding measurement delay, Ref. [25] presented an ensemble methodology using the Kalman filter and nearest neighbor algorithm. Ref. [26] presented a state estimation method (Diffusion Map Kalman (DMK)) for the stochastic environment. The DMK-based UAV tracking model was designed by combining a Diffusion Map (DM) [27,28] and KF [29–31] with minimum prior knowledge of the tracking system. By using a diffusion map dimension, the size of the parameter is reduced, aiding the measurement model of DMK. Nonetheless, when noise and uncertainty are introduced into the model, the accuracies of tracking drones are significantly reduced. Refs. [32,33] showed that Regularized Least Squares (RLS) using the KF is efficient when noise is introduced into the model. However, these models are not efficient for tracking drones; this is because drones exhibit high uncertainty in their mobility. Thus, for modeling such uncertainty in the measurement model under a stochastic environment, this manuscript presents an error-aware Kalman filter (UEAKF) employing RLS for tracking drones.

The significance of the proposed UEAKF based UAV tracking model is described below:

- UEAKF considered estimation dynamics for incorporating behavior traits into the measurement methodology by noise organize stochastically through unconditional parameter.
- The UEAKF UAV tracking model achieves much better RMSE performance in comparison with the PF-based and DMK-based UAV tracking model under a stochastic environment.

The remainder of this manuscript is organized as follows: In Section 2, the unmanned aerial vehicle tracking model using the uncertainty and error-aware Kalman filter algorithm in unknown and noisy environments is presented. In Section 3, the experimental outcomes of the proposed UEAKF and existing UAV tracking outcomes in terms of error metric are measured; and in the last section, the work is concluded and future work is defined for further improving UAV tracking performance.

2. Tracking of Unmanned Aerial Vehicles Using Uncertainty and Error-Aware Kalman Filter Algorithm

This paper presents the tracking of an unmanned aerial vehicle using uncertainty and error-aware Kalman Filter methodologies. First, the section discusses the standard KF algorithm used for tracking UAVs. Then, it discusses the problem involved using existing KF for modeling the uncertainty of UAVs. Furthermore, it presents the UEAKF for more efficiently modeling the uncertainty of UAVs, aiding in improving tracking performance in the stochastic system (Algorithm 1).

2.1. Kalman Filter Algorithm

Let us consider a stochastic unmanned aerial vehicle tracking system as follows:

$$y_{l+1} = B_l y_l + \delta_l x_l, \tag{1}$$

$$z_l = I_l y_l + w_l \alpha_l. \tag{2}$$

For $l \geq 0$, where $\delta_l \in \mathbb{S}^{o*n}$, $w_l \in \mathbb{S}^{q*0}$, $B_l \in \mathbb{S}^{o*o}$, and $I_l \in \mathbb{S}^{q*o}$ outline the accurately known matrices; $y_l \in \mathbb{S}^o$ defines the state vector; x_l, α_l represents the zero-mean Gaussian process that is multidimensional, uncorrelated, with improved covariance; $S_l = w_l w_l'$ signifies the respective measurements; and $R_l = \delta_l \delta_l'$ defines the model's noise covariance.

The Kalman filter updating phase is acquired by utilizing the respective association described in the equations

$$H \leftarrow Q^{-1}_{l|l-1}, \tag{3}$$

$$H \leftarrow Q^{-1}_{l|l-1}, \tag{4}$$

$$w \leftarrow \hat{y}_{l|l} - \hat{y}_{l|l-1}, \tag{5}$$

$$G \leftarrow I_l, \tag{6}$$

$$a \leftarrow z_l - I_l \hat{y}_{l|l-1}. \tag{7}$$

The estimation problem usually relies on solving RLS. Let us consider that there is a necessity for establishing an unidentified vector $y \in \mathbb{S}^q$ from the measurement $z = Gy + \alpha$, where $x \in \mathbb{S}^q$ and α represents the noise. Let us assume that the tracking model previously knows certain information such as $\overline{y} \in y$ and the configuration $w = y - \overline{y}$, $a = z - G\overline{y}$, where w describes the approximation variance and a defines the difference. The regularized least regressive problem [32,33] is obtained as follows:

$$\min_{w} \Big[w' H_w + (G_{w-a})' X (G_w - a) \Big], \tag{8}$$

$G \in \mathbb{S}^{q*0}$ and $H = H' \succ 0$, $X = X' \succ 0$ signify dimensional matrices. The ideal scheme of Equation (8), considering G and a are precisely known, is estimated using the following equation:

$$w^* = \left[H + G'XG\right]^{-1} G'X_a. \tag{9}$$

Therefore, using Equation (9), the following Kalman filter equation is obtained:

$$\hat{y}_{l|l} = \hat{y}_{l|l-1} + L_l\left(z_l - I_l\hat{y}_{l|l-1}\right), \tag{10}$$

$$L_l = Q_{l|l} I_l' S_l^{-1}, \tag{11}$$

$$Q_{l|l} = \left(Q_{l|l-1}^{-1} + I_l' S_l^{-1} I_l\right)^{-1}. \tag{12}$$

Algorithm 1 UEAKF.

Step 01. First, similar to the standard KF, employ linearization closer to the equilibrium point.
Step 02. Identify the noise and approximate the residual errors.
Step 03. Build a measurement model using environment matrices and measurement matrices without prior information.
Step 04. The data obtained in previous step define the measurement, the state estimation, and the respective covariance.
Step 05. Prediction phase.
Step 06. The state estimation and its covariance of initial states are known information.
Step 07. More care is taken to measure the covariance of respective prediction model because of state-dependent noise.
Step 08. Updation phase.
Step 09. Modified estimation model of the standard KF by introducing and estimating the variance argument.
Step 10. Modeling uncertainties and error into UEAKF by introducing noise into the measurement model.
Step 11. The covariance matrix with constraint is computed for error update.

2.2. *Uncertainty and Error-Aware Kalman Filter Algorithm*

Here, utilizing the inverse matrix condition described in Equation (12), the iterative equation is obtained. Existing methodologies were generally designed using the KF for addressing UAV problems; however, KF- based UAV tracking methodologies are not efficient when introduced in a highly uncertain environment considering minimal or no prior information. To address this problem, this work introduced UEAKF (Figure 4) for the nonlinear environment is obtained as follows:

$$y_{l+1} = g(y_l) + \delta x_l \tag{13}$$

and its measurement is obtained as follows:

$$z_l = i(y_l) + w\alpha_l. \tag{14}$$

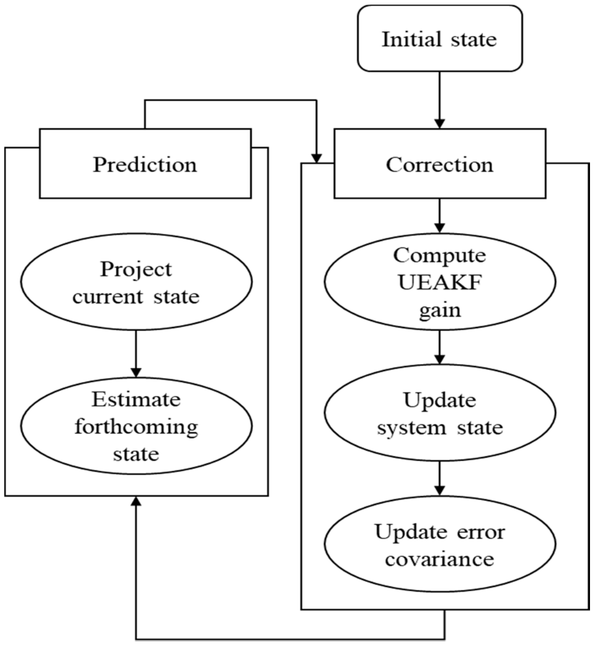

Figure 4. Block diagram of UEAKF.

Next, we identify the noise and approximate the residual errors using the following equations:

$$y_{l+1} = By_l + \delta x_l + \left(\delta_y + \overline{\delta}_y \mathcal{D}(|\widetilde{y}_l|)\right)\alpha_l^y, \tag{15}$$

$$z_l = Iy_l + w\alpha_l + \left(\delta_z + \overline{\delta}_z \mathcal{D}(|\widetilde{y}_l|)\right)\alpha_l^z \tag{16}$$

Here, B describes system matrices and I measurement matrices with no prior knowledge; and δ_y, $\overline{\delta}_y$, δ_z, and $\overline{\delta}_z$ are UEAKF matrices. The sequence set x_l, α_l^y, α_l, and α_l^z, l, 0 signifies the Gaussian with zero mean and the uniform covariance and $\delta\delta^U \succ 0, ww^U \succ 0$. The UEAKF is built utilizing state estimation and its covariance in the prediction and update phase. The information collected at phase l defines the measurement z_l, the state estimation $y_{l|l}$, and the corresponding covariance $Q_{l|l}$. The anticipated trajectory is obtained using the following equation.

$$F\left\{\cdot \middle| z_l, \hat{y}_{l|l}, Q_{l|l}\right\} = F_l\{\cdot\} \tag{17}$$

2.3. Prediction Phase

To measure the error covariance matrix, more care should be used by the estimator due to state-dependent noise. Let us consider $Y_l = Y_l\{\mathcal{D}(|y_l|)\}$. Considering the tracking system defined in Equation (15), the covariance of the corresponding projection model $\hat{y}_{l+1|l} = F_l\{y_{l+1}\}$ is

$$Q_{l+1|l} = BQ_{l|l}B^U + R_l, \tag{18}$$

$$R_l = \delta\delta^U + \delta_y\delta_y^U + \overline{\delta}_y \mathcal{D}\left(Q_{l|l} + \hat{y}_{l|l} + \hat{y}_{l|l}\hat{y}_{l|l}^U\right)\overline{\delta}_y^U \tag{19}$$

2.4. Updating Phase

The update phase estimation $\hat{y}_{l+1|l+1}$ for the standard KF is obtained as follows:

$$\min_y \left(||y - \hat{y}_{l+1|l}||^2 + ||z_{l+1} - I_y||^2_{S^{-1}} \right) \tag{20}$$

where $S = ww^U \succ 0$. Furthermore, for making Equation (20) meaningful in Equation (19), here, $R_l \succ 0$; thus, the expected estimates are acquired as follows:

$$\hat{y}_{l+1|l+1} = \hat{y}_{l+1|l} + w^* \tag{21}$$

where w^* signifies the argument of the UEAKF estimation model, which is described using the following equation:

$$w^* = \arg\min_{w} \left(||w||^2_{Q^{-1}_{l+1|l+1}} + ||a_{l+1} - I_w||^2_{S^{-1}} \right), \tag{22}$$

where w defines the estimate variance and a_{l+1} describes the UEAKF estimation model. Thus, the UEAKF update model is attained as follows:

$$\hat{y}_{l+1|l+1} = \hat{y}_{l+1} + L_{l+1}\left(z_{l+1} - I\hat{y}_{l+1|l}\right) - M_{l+1}\gamma_{l+1}. \tag{23}$$

2.5. Covariance Matrix

Here, for obtaining the covariance matrix of Equation (21), it must fulfill the bound described below:

$$\begin{aligned} &Q_{l+1|l} - L_{l+1}\left[\overline{\delta}_z \mathcal{D}\left(Q_{l+1|l+1}\right)\overline{\delta}_z^U + \delta_z Y_{l+1}\overline{\delta}_z + \overline{\delta}_z Y_{l+1}\delta_z\right] L^U_{l+1} \\ &= (J - L_{l+1}I)Q_{l+1|l}(J - L_{l+1}I)^U + L_{l+1}\widetilde{S}_{l+1}L^U_{l+1} + \beta_{l+1}\mu_l\beta^U_{l+1}. \end{aligned} \tag{24}$$

The UEAKF in Equations (15), (18), (23) and (24) for tracking unmanned aerial vehicles is modeled with the updating parameter $\delta_w = \delta_z$ and $\overline{\delta}_w = \overline{\delta}_z$, and is executed together with other existing KF-based UAV tracking methodologies. The UEAKF can achieve better tracking performance considering lower and higher noise levels compared to other standard algorithms such as PF-based and DMK-based UAV tracking methodologies, which is experimentally proven below.

3. Simulation Analysis and Result

We conducted experiments for validating the UAV tracking outcome of the UEAKF, PF [34], and DMK [26] in terms of RMSE. The performance was measured considering highly uncertainty and nonlinear UAV tracking environments. Through experiment analysis, this work shows that the UEAKF obtains much-improved state estimation compared to DMK-based and PF-based UAV tracking methodologies.

For evaluating the performance of the UEAKF, we considered a highly uncertain and noisy UAV trajectory. A sample representation of the UAV path is provided in two-dimensional spaces, as shown in Figures 5 and 6, which was used for experiment analysis. The two-dimensional space was measured using the radius and azimuth angle; signal length = 1000; time step = 0.01 s, standard deviation of the process noise = 0.18, 0.67, 1.5, and 2.5; and the number of process generation iterations for RMSE calculations = 50 (Figure 7 shows the flowchart for illustrating the UEAKF UAV/drone's position). The respective function defining the Cartesian location of the unmanned aerial vehicle at a different instance in time is defined as a discrete time using the following equation [26]:

$$\Delta\theta^{(1)}_{n+1} = -\frac{1}{2}\left(\theta^{(1)}_n - 1\right)^3 + \left(\theta^{(1)}_n - 1\right) + \sqrt{2}u^{(1)}_n \tag{25}$$

$$\Delta\theta^{(2)}_{n+1} = -\frac{1}{2}\left(\theta^{(2)}_n - 6\right)^3 + \left(\theta^{(2)}_n - 6\right) + \sqrt{2}u^{(2)}_n \tag{26}$$

where $u_n^{(1)}$ and $u_n^{(2)}$ depict Gaussian noise (GN) and define double-well capabilities. The location of unmanned aerial vehicles is estimated utilizing the radius and azimuth angle within polar coordinates using the following equations:

$$\varnothing_n = \text{arc}\ \tan\left(\frac{\theta_n^{(1)}}{\theta_n^{(2)}}\right), r_n = \sqrt{\left(\theta_n^{(1)}\right)^2 + \left(\theta_n^{(1)}\right)^2}, \tag{27}$$

and by introducing GN, the unmanned aerial vehicle measurement is produced using the following equation:

$$Z_n = \left[\varnothing_n + v_n^{(\varnothing)}, r_n + v_n^{(r)}\right], \tag{28}$$

where $v_n^{(\varnothing)}$ is GN function with variance $\sigma_\varnothing^2$, and $v_n^{(r)}$ is a GN function with variance σ_r^2. Hereby considering an interval time Δt of 0.01, we constructed 1000 trajectories samples. Then, tracking performance was measured by applying the UEAKF, PF, and DMK concurrently to measure z_n by varying $\sigma_\varnothing^2$ and σ_r^2 (i.e., signal-to-noise levels) for evaluating the tracking performance of different models.

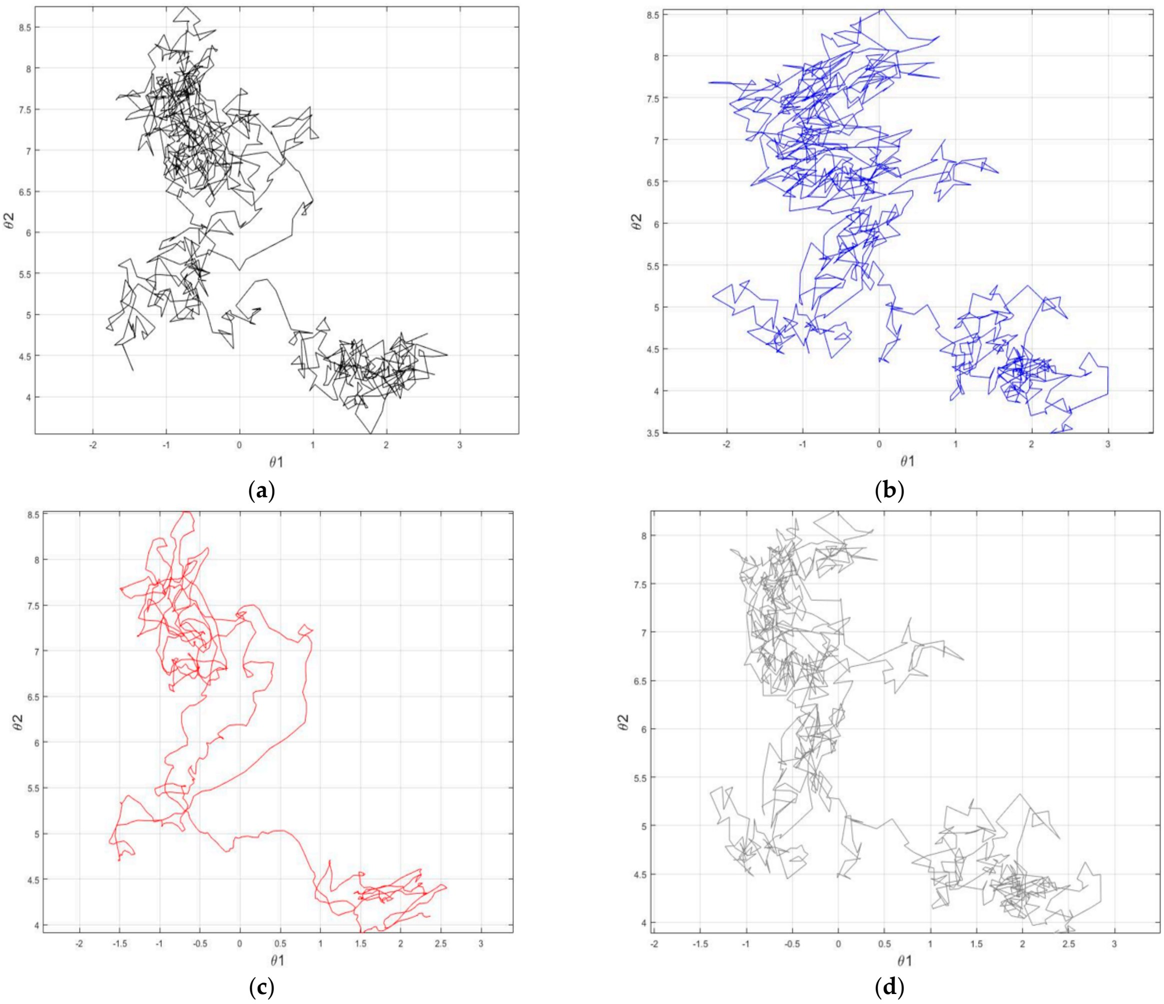

Figure 5. Different models' paths in 2D: (**a**) clean data [26], (**b**) DMK drone path, (**c**) PF drone path, and (**d**) UEAKF drone path.

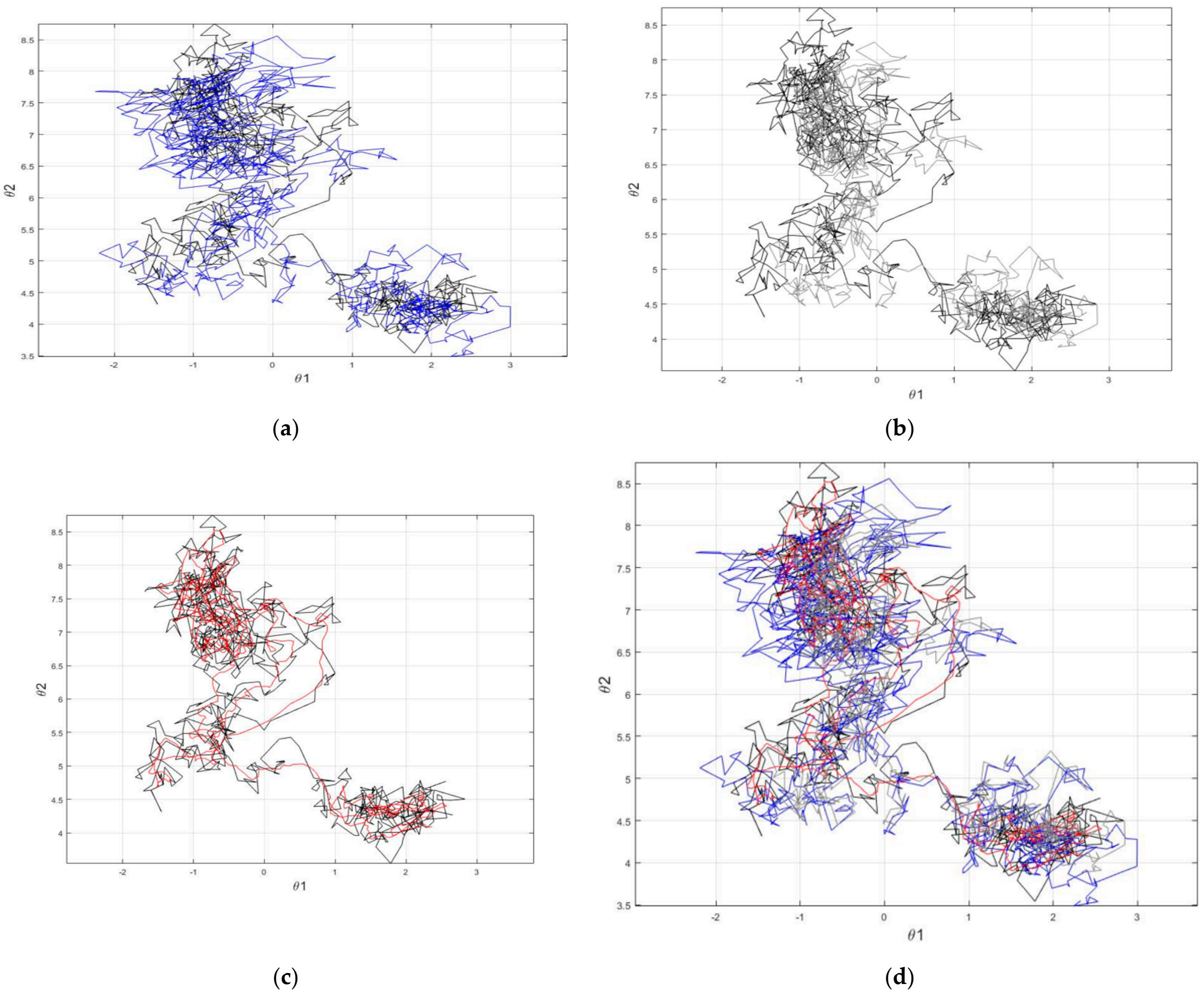

Figure 6. Tracking path predicted by different UAV tracking methodologies: (**a**) real drone path vs. DMK, (**b**) real drone path vs. PF, (**c**) real drone path vs. UEAKF, (**d**): UEAKF, DMK, and PF vs. real drone path.

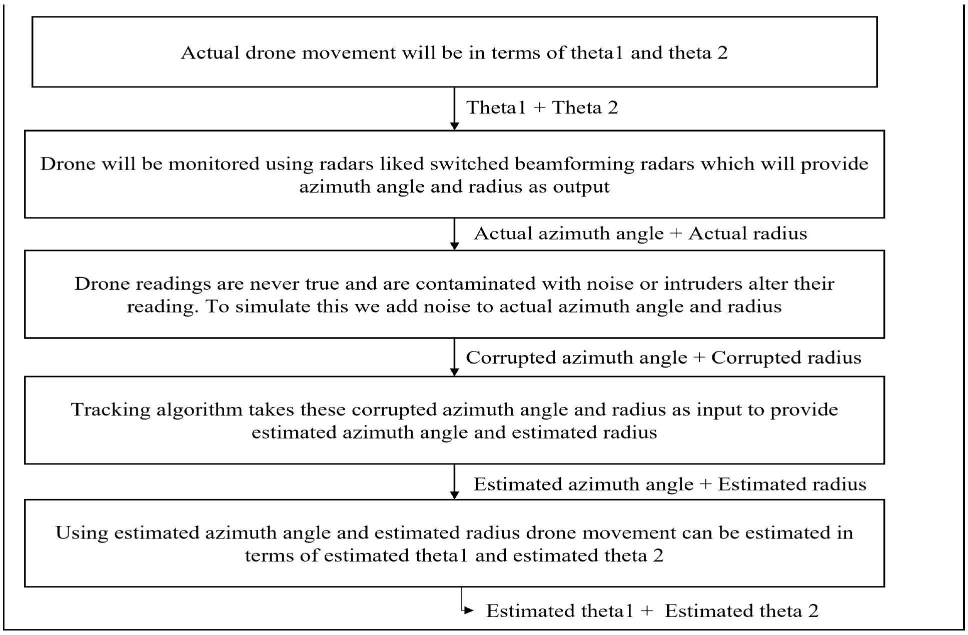

Figure 7. Flowchart for UAVs/drones position tracking.

Figures 8 and 9 show the RMSE results achieved with respect to a clean estimate by different algorithms such as the UEAKF-, PF-, and DMK-based UAV tracking methodologies. Using a logarithm scale, the RMSE outcome was computed: the $\varnothing_n$ and r_n obtained by the respective tracking methodologies and measurement error as an upper bound. Here, the SNR level was varied and RMSE performance was measured, and the mean and standard deviation of the RMSE were estimated considering 50 samples. The average RMSE obtained by different filtering methodologies is shown in Figures 10 and 11. Figure 10 shows the measurement of r_n and Figure 11 shows the measurement of $\varnothing_n$. Figures 8–11 show that both PF and DMK achieved similar RMSE performance. In some cases, PF performed slightly better than the DMK; this is because DMK error was present in the tracking model and was affected when high noise was introduced. From the overall result achieved, we found that UEAKF achieves a much better tracking performance in comparison to PF and DMK when considering lower and higher levels of noise.

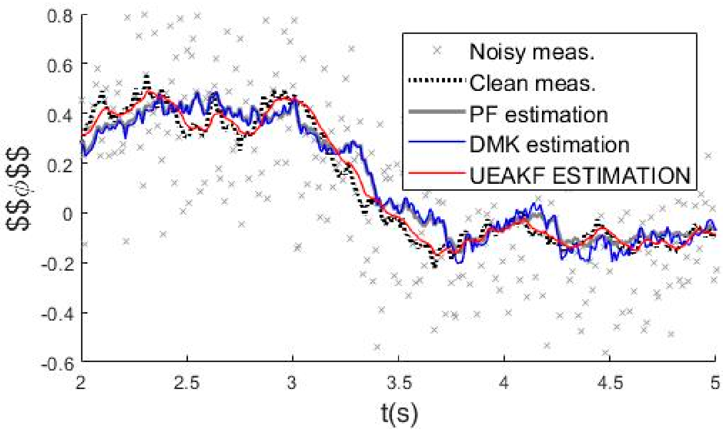

Figure 8. $\varnothing_n$ mean and standard deviation of the nRMSE of the clean measurement estimations.

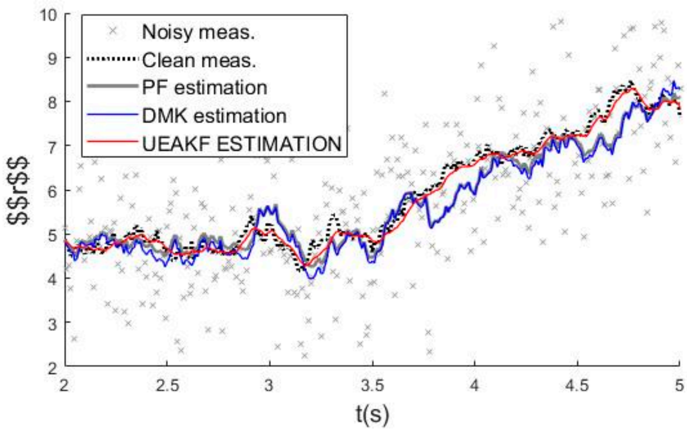

Figure 9. r_n standard deviation and mean of the nRMSE of the clean measurement estimations. The nRMSE outcomes were averaged over 50 samples of process and noise trajectories.

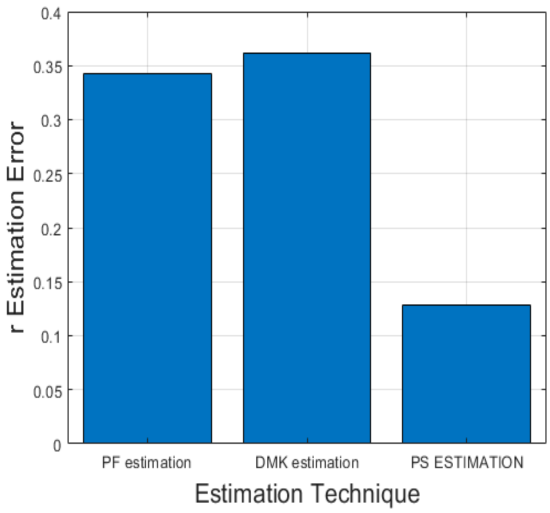

Figure 10. Average RMSE obtained for the measurement of r_n.

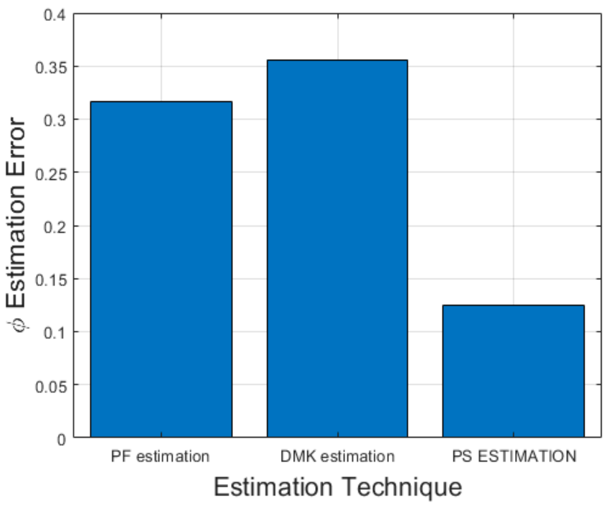

Figure 11. Average RMSE obtained for the measurement of $\varnothing_n$.

4. Conclusions

This paper first discussed the challenges involving tracking UAVs using radars considering stochastic environments. From this study, we found that the state-of-art particle- and Kalman-based filtering methodologies achieve poor estimation outcomes or even cause divergence in noisy environments. Introducing a diffusion map into the KF aided in improving the UAV tracking performance in a multidimensional nonlinear stochastic environment. The DMK model is nonparametric and captures semantic feature using noisy measurement without any prior knowledge of the environment. The DMK model works well in a limited noisy environment; however, when adopted for extremely noisy conditions, the DMK performs poorly compared to the PF. For addressing these issues, we presented a robust estimation model, namely UEAKF, for tracking UAVs using radar by introducing random noise into the tracking environment. The UEAKF tries to create tradeoffs between achieving the optimal preceding estimate with respect to maximizing forthcoming measurement estimates considering the Gaussian assumption. By using RLS, the uncertainty of the environment is captured more efficiently; thus, we found our proposed method is robust in nature even when used in unknown and noisy environments. The simulation outcome showed that the proposed UAEKF can achieve higher accuracy (i.e., RMSE) in tracking UAVs compared to the PF- and DMK-based UAV tracking models.

Tracking drone's does not guarantee security: there are cases where different drones exhibit different signatures, and where some attempt to imitate the signature of another drone to escape from tracking; thus, in the future, it is important to design an efficient drone signature tracking and detection mechanism to mitigate the impacts of the actions of malicious drones.

Author Contributions: M.A.A.-A. and A.A.A.-A. contributed to the main idea and the methodology of the research; M.A.A.-A. designed the experiment, performed the simulations, and wrote the original manuscript; R.F., A.A.A.-A., K.-H.K. and Y.-S.L. contributed significantly to improving the technical and grammatical content of the manuscript; A.A.A.-A., M.A.A.-A. and H.-J.L. reviewed the manuscript and provided valuable suggestions to further refine the manuscript. All authors have read and agreed to the published version of the manuscript.

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