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Research Article

Unscented Kalman filter based attitude estimation of a quadrotor

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Abstract

Quadrotors are well - known unmanned aerial vehicle structures that have some advantages such as hovering, vertical take – off and landing, and low – speed flight. On the other hand, quadrotors are subjected to modeling and sensor uncertainties that lead to erroneous state estimation. Kalman filter has been proven to be the optimal estimator for the Gaussian distributed noise for linear processes. However, linear dynamical models of the quadrotors are not accurate representations of the systems due to nonlinearities, and coupling between the states. Extended Kalman filter (EKF) is proposed to solve the above issue. But, first order Taylor series approximation for the nonlinear state model may lead inefficiencies. For this reason, another Kalman filter framework is proposed that employs unscented transformation (UT). Unscented Kalman filter (UKF), can model the state distribution as Gaussian random variable to the third degree for arbitrary nonlinearities.

So, in this study, unscented Kalman filter based estimation scheme is presented to overcome the sensor and model noises for nonlinear quadrotor attitude dynamics. According to the statistical analysis, the approach can estimate and reduce the mean absolute error, root mean square error and also variance of the noise for all attitude states.

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Bir dönerkanadın UKF tabanlı durum kestirimi

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Öz

Döner kanatlar, havada asılı kalabilme, dikey iniş kalkış yapabilme ve düşük hızlarda uçabilme özelliklerine sahip iyi bilinen bir insansız hava aracı türüdür. Fakat, döner kanatlar hatalı durum kestirimine yol açan modelleme ve sensör hatalarına maruz kalmaktadırlar. Kalman filtresi, Gauss dağılmış rassal gürültüye sahip doğrusal sistemler için eniyiliği kanıtlanmış bir filtredir. Bununla birlikte, durum değişkenleri arasındaki etkiler ve doğrusallıktan uzak denklemlerden dolayı döner kanatların doğrusal modellenmesi gerçeği yansıtmamaktadır. EKF bu sorunu çözmek için önerilen bir filtredir. Fakat, doğrusal olmayan sistemlerin birinci dereceden Taylor serisi ile yaklaşımı yetersiz kalabilmektedir. Bu sebeple, UT ye dayanan başka bir Kalman filtresi önerilmiştir. UKF, durum dağılımını Gauss rassal değişkeni olarak üçüncü dereceden herhangi doğrusal olmayan durum için modelleyebilmektedir.

Bu çalışmada, doğrusal olmayan döner kanat durum dinamikleri için bahsedilen ölçüm ve modelleme hatalarına çözüm amaçlı UKF tabanlı kestirimci gerçeklenmiştir. İstatistiksel analiz sonuçlarına göre, yaklaşım gürültüleri kestirebilmekte ve MAE, RMSE hataları ile gürültü varyansını tüm durum değişkenleri için düşürebilmektedir.

Bu çalışma Eskişehir Teknik Üniversitesi Bilimsel Araştırma Projeleri Komisyonu tarafından kabul edilen 20ADP229 nolu proje kapsamında desteklenmiştir.

1. INTRODUCTION

Quadrotor is a type of rotorcraft that belongs to the subcategory of unmanned aerial vehicles. Quadrotors have some capabilities such as hovering, vertical take – off and landing, low – speed flight where fixed – wing unmanned aerial vehicles fall short. Due to aforementioned advantages, a big research effort went into the modeling, control and estimation of the quadrotor environment and applications of quadrotors has spread over different areas such as commercial, hobby rc, and military. Some applications of quadrotors can be observed in aerial video and imaging, survaillance, search and rescue, inspection and so on.

The quadrotor has four independent rotors on the edges of the rigid body frame. There exist several quadrotor types, such as (x) frame or (+) frame, that differs how the rotors are placed on the body frame. The quadrotor is an underactuated dynamical plant since it has four inputs in six degree – of – freedom space. So, full control of the quadrotor needs special techniques such as cascading controllers that comprise of inner and outer loops. While the inner loop corresponds to rotational dynamics, the outer loop corresponds to translational dynamics. With this implementation technique, some attitude states of the quadrotor can be controlled by some translational states which compansates the underactuated environment.
In despite of numerous advantages, quadrotors generally suffer from low – cost sensor noises that deteoriates the performance and even causes instability issues on quadrotor control. So as to overcome the undesired noise problem, an observer [1] scheme is needed. Amongst many filter structures, Kalman filter is widely used for state estimation purposes since it ensures mean square error optimality when a noise is distributed as Gaussian random variable.

Kalman filter, proposed by [2], employs the state – space model of the plant and measurement dynamics with a priori known mean and covariance values. A Kalman filter can handle Gaussian distributed measurement noises as well as modeling uncertanities for linear processes. There are numerous studies related to Kalman filter based state estimation of unmanned aerial vehicles, aircrafts, satellites and quadrotors. Aircraft icing detection, identification and control with Kalman filter and neural networks is proposed in [3]. A Kalman filter based attitude estimation scheme is presented in [4] for linear quadrotor attitude dynamics. An improved attitude estimation algorithm based on the fusion of complementary filter and Kalman filter is given in [5] for an indoor quadrotor. An optimal Kalman filter for state estimation of a quadrotor is studied in [6]. A hybrid optimal Kalman filter scheme is proposed in [7] for three dimensional position estimation of a quadrotor. However, standard Kalman filter can not deal with the nonlinear plant dynamics since it is derived for the linear processes.

An improvement to the Kalman filter to cover the nonlinear dynamical equations is achieved by extended Kalman filter algorithm where nonlinear dynamics are linearized around the equilibrium point at time instances with 1st degree – Taylor series expansion. Extended Kalman filter based state vector estimation of a quadrotor in vertical flight is presented in [8]. An extended Kalman filter for special Euclidean group SE(3) is derived in [9] for geometric control of a quadrotor. An optimized Kalman filter and extended Kalman filter is proposed in [10] for nonlinear attitude dynamics of a quadrotor. Joint estimation of state and parameter of a quadrotor is given in [11] with an extended Kalman filter and complementary filter. An extended Kalman filter is derived in [12] for quadrotor state estimation of asyncronous multisensor data. But, extended Kalman filter may give unsatisfactory results when the system has strong nonlinearities.

A Kalman filter scheme incorparating unscented transform is developed to address the nonlinearity issue considered above. Unscented Kalman filter can approximate any Gaussian random variable with arbitrary nonlinearities to 3rd degree. Unscented Kalman filter based nonlinear estimation of a quadrotor is given in [13]. Another unscented Kalman filter is given in [14] for the orientation module of a quadrotor. An unscented Kalman filter based state estimation is given in [15] for manipulating unmanned aerial vehicles. An improved unscented Kalman filter with robustness property is proposed in [16] for attitude estimation of a pico satelite. A joint unscented Kalman filtering scheme is proposed in [17] for parameter estimation of nonlinear systems. An improved robust derivative unscented Kalman filter to cover the non – Gaussian noises is proposed in [18]. So, unscented Kalman filter based estimation schemes have being widely employed into the state estimation of aerial vehicles and developments on unscented Kalman filter lead more accurate estimation performances.

Based on the above survey, an unscented Kalman filter based attitude estimation scheme is presented in this paper since unscented Kalman filter offers superior performance at the same computational cost with the extended Kalman filter and enhances the classical Kalman filter algorithm to nonlinear dynamics. The estimation scheme is tested with both process and measurement noise for attitude states of the quadrotor. The performance analysis is studied with root mean square error, mean absolute error, and variance of error metrics.

The remainder of the paper is as follows. Mathematical model of the nonlinear quadrotor attitude dynamics is derived in Section 2. Unscented Kalman filter based estimation scheme is given in Section 3. Results and discussions are covered in Section 4. Lastly, conclusions are deriven in Section 5.

2. QUADROTOR MODEL

A quadrotor has four upward facing rotors that are attached to the rigid frame. Six degree – of – freedom space of the quadrotor can be divided into two groups: rotational and translational motions. Rotational motion can be represented by Euler angles $\boldsymbol{\eta} = \{\phi, \theta, \psi\}$ where ϕ is roll angle, θ is pitch angle and ψ is yaw angle. Translational motion can be represented by a position vector $\boldsymbol{\xi} = \{x, y, z\}$.

A typical quadrotor, its axes, and defined Euler angles are given in Figure 1 where **B** denotes body frame and **I** denotes inertial frame. Both **B** and **I** are three dimensional spaces and their axes are $\{x_b, y_b, z_b\} \in \mathbb{R}^3$ for **B** and $\{x_i, y_i, z_i\} \in \mathbb{R}^3$ for I, respectively. Lets define the linear velocity vector as $\boldsymbol{\varsigma} = \{\varsigma_1, \varsigma_2, \varsigma_3\} \in \mathbb{R}^3$ and angular velocity vector as $\boldsymbol{\Omega} = \{\Omega_1, \Omega_2, \Omega_3\} \in \mathbb{R}^3$. A rotation matrix is needed in order to transform any vector from one frame to another frame. Such a transformation is achieved by the matrix given in Equation 1.

$$R_b^i = \begin{bmatrix} c\theta c\psi & s\theta s\phi c\psi - s\psi c\phi & s\theta c\phi c\psi + s\psi s\phi \\ c\theta s\psi & s\psi s\theta s\phi + c\psi c\phi & s\psi s\theta c\phi - c\psi s\phi \\ -s\theta & s\phi c\theta & c\phi c\theta \end{bmatrix} \quad (1)$$

where R_b^i denotes the transformation between body and inertial frames, $c()$ and $s()$ are the abbreviations of cos and sin, respectively. Note that Euler angles must obey the Equation 2 to prevent any singularities.

$$\theta \in (-\tfrac{\pi}{2}, \tfrac{\pi}{2}), \phi \in (-\tfrac{\pi}{2}, \tfrac{\pi}{2}), \psi \in (-\pi, \pi) \quad (2)$$

Also, reverse transformation can be achieved by Equation 3.

$$\bar{\boldsymbol{R}}_b^i = \begin{bmatrix} 1 & 0 & -s\theta \\ 0 & c\phi & s\phi c\theta \\ 0 & -s\phi & c\phi c\theta \end{bmatrix} \quad (3)$$

By using Equations 1 and 3, kinematic model of the quadrotor can be given in Equation 4.

$$\begin{cases} \dot{\xi} = R_b^i \varsigma \\ \dot{\eta} = \bar{R}_b^i \Omega \end{cases} \quad (4)$$

The total forces and torques that act on a quadrotor is given in Equation 5 with the aid of Newton – Euler formalism.

$$\begin{cases} \sum \boldsymbol{F} = m\dot{\boldsymbol{\varsigma}} + \boldsymbol{\Omega} \times (m\boldsymbol{\varsigma}) \\ \sum \boldsymbol{\tau} = \boldsymbol{J}\dot{\boldsymbol{\Omega}} + \boldsymbol{\Omega} \times (\boldsymbol{J}\boldsymbol{\Omega}) \end{cases} \quad (5)$$

where $\boldsymbol{F}$ is force, $\boldsymbol{\tau}$ is torque, $\boldsymbol{J} \in \mathbb{R}^{3x3}$ is the inertia matrix, and m is mass of the quadrotor, respectively. Since quadrotor frame is assumed to be symmetrical, the inertia matrix $\boldsymbol{J}$ can be defined as follows.

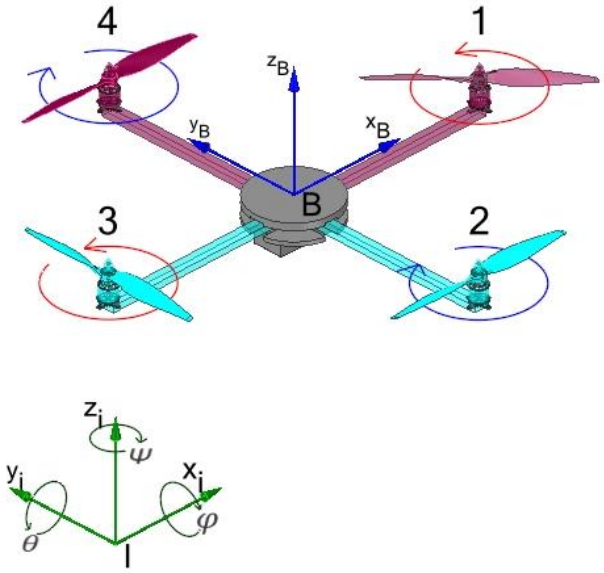


Figure 1. Quadrotor, body and inertial axes

$$\boldsymbol{J} = \begin{bmatrix} I_{xx} & 0 & 0 \\ 0 & I_{yy} & 0 \\ 0 & 0 & I_{zz} \end{bmatrix} \quad (6)$$

where I_{xx}, I_{yy}, I_{zz} are the principal moment of inertias.

Three degree – of – freedom attitude model of the quadrotor can be obtained in Equation 7 with taking the time derivative of Equation 4 and using Equation 5 as follows.

$$\begin{aligned} \ddot{\boldsymbol{\eta}} = {} & \bar{\boldsymbol{R}}_i^b \boldsymbol{J}^{-1} \boldsymbol{\tau}_{rot} - \bar{\boldsymbol{R}}_i^b \boldsymbol{J}^{-1} \left(\bar{\boldsymbol{R}}_b^i \dot{\boldsymbol{\eta}} \times \boldsymbol{J} \bar{\boldsymbol{R}}_b^i \dot{\boldsymbol{\eta}} \right) \\ & - \bar{\boldsymbol{R}}_i^b \boldsymbol{J}^{-1} \boldsymbol{K}_r \bar{\boldsymbol{R}}_b^i \dot{\boldsymbol{\eta}} \\ & - \bar{\boldsymbol{R}}_i^b \left(\frac{\partial \bar{\boldsymbol{R}}_b^i}{\partial \phi} \dot{\phi} + \frac{\partial \bar{\boldsymbol{R}}_b^i}{\partial \theta} \dot{\theta} \right) \dot{\boldsymbol{\eta}} - \boldsymbol{\tau}_{dis} \end{aligned} \quad (7)$$

where $\boldsymbol{\tau}_{rot}$ is torque vector, $\boldsymbol{\tau}_{dis}$ is disturbance torque, b is thrust coefficient, d is drag coefficient, l is length of motor arm, $\boldsymbol{G}$ is gravitational force vector, respectively. A more detailed derivation of the quadrotor dynamical model can be found in [19].

3. ESTIMATION METHOD

The need for an extension to the nonlinear processes leads to the development of the extended Kalman filter estimator. In the extended Kalman filter, distribution of the state is approximated by a Gaussian random variable. This approximation is then analytically propagated through the 1st order linearized Taylor series. However, if dynamical system has strong nonlinearities that can not be expressed by linearization, the output of the filter may lead to sub – optimal performance and even may cause the divergence of the filter. On the other hand, thanks to the unscented transformation, the approximated state distribution is represented with a minimal set of carefully chosen points where they are called as sigma - points [20]. These sigma – points can completely capture the mean and covariance of the approximated

Gaussian random variable and after the nonlinear transformation, can capture the posterior mean and covariance to the 3rd order Taylor series expansion for arbitrary nonlinearity [21].

Consider that discrete nonlinear quadrotor dynamics with the additive noise are given in Equation 8 as follows.

$$x_{k+1} = f_k(x_k) + w_k$$
$$y_k = h_k(x_k) + v_k \quad (8)$$

where $x_k, x_{k+1} \in \mathbb{R}^3$ is the state vector, $f_k: \mathbb{R}^3 \rightarrow \mathbb{R}^3$ is the nonlinear state function, $y_k \in \mathbb{R}^3$ is the output vector, $h_k: \mathbb{R}^3 \rightarrow \mathbb{R}^3$ is the measurement function, w_k is process noise and v_k is measurement noise, k is the time instance, $x_k = [\phi, \theta, \psi]^t$ and $y_k = [\phi, \theta, \psi]^t$, respectively.

A random variable x can be propogated by using the nonlinear state function given in Equation 8. Let the expected value of the x is $E[\mathrm{x}] = \bar{\mathrm{x}}$ and the covariance of the x is $E[(\mathrm{x} - \bar{\mathrm{x}})(\mathrm{x} - \bar{\mathrm{x}})^t] = \mathbf{P}_{\mathrm{x}}$. The statistics of the propogated random variable can be calculated via the unscented transformation. Firstly, a matrix χ with dimension of $2n + 1$ is formed in Equation 9 where n is the dimension of the random variable x.

$$\chi_0 = \bar{\mathrm{x}}$$
$$\chi_i = \bar{\mathrm{x}} + \left(\sqrt{(n+\lambda)\mathbf{P}_{\mathrm{x}}}\right)_i \quad i = 1, \dots, n \quad (9)$$
$$\chi_i = \bar{\mathrm{x}} - \left(\sqrt{(n+\lambda)\mathbf{P}_{\mathrm{x}}}\right)_{i-n} \quad i = n+1, \dots, 2n$$

where χ_i are the sigma vectors, $\lambda = \alpha^2(n + \kappa) - n$, α is a constant that determines the spread of the χ_i around $\bar{\mathrm{x}}$, κ is secondary scaling parameter, and $\left(\sqrt{(n+\lambda)\mathbf{P}_{\mathrm{x}}}\right)_i$ is the ith. row of the matrix square root. α is generally set to $1E-3$ while κ is set to 0, respectively. The associated weights of the χ matrix can be costructed by Equation 10 as follows.

$$W_0^m = \frac{\lambda}{(n + \lambda)}$$
$$W_0^c = \frac{\lambda}{(n + \lambda)} + (1 - \alpha^2 + \beta) \quad (10)$$
$$W_i^m = W_i^c = \frac{1}{2(n + \lambda)} \quad i = 1, \dots, 2n$$

where W_i is the corresponding weigth of the χ_i, β is a coefficient to incorporate the prior knowledge of the distribution of the random variable x [21]. The value of β is to be changed according to the considered distributions whereas its optimal value is 2 for Gaussian distributions. The nonlinear transformation of the sigma vector is now can be obtained through the Equation 11.

$$\gamma_i = f(\chi_i) \quad (11)$$

where $i = 1,2, \dots, 2n$. With the help of the transformed vector γ, approximated mean y is calculated as below.

$$\bar{y} \approx \sum_{i=0}^{2n} W_i^m \gamma_i \quad (12)$$

The covariance of y can be approximated as follows.

$$\mathbf{P}_{\mathrm{y}} \approx \sum_{i=0}^{2n} W_i^c (\gamma_i - \bar{y})(\gamma_i - \bar{y})^t \quad (13)$$

Using the notation above, equations of the unscented Kalman filtering scheme can be summarized for the zero mean additive noise in Equations 14 – 26 [20]. Note that for the non – additive case, the state vector x must be augmented with the process and measurement noise, respectively.

Initialization of the filter scheme ($k = 0$):

$$\tilde{x}_0 = E[x_0] \quad (14)$$
$$\mathbf{P}_0 = E[(x_0 - \tilde{x}_0)(x_0 - \tilde{x}_0)^t] \quad (15)$$

Calculation of sigma points ($k = else$):

$$\chi_{k-1} = [\tilde{x}_{k-1},$$
$$\tilde{x}_{k-1} + \left(\sqrt{(n+\lambda)\mathbf{P}_{k-1}}\right), \quad (16)$$
$$\tilde{x}_{k-1} - \left(\sqrt{(n+\lambda)\mathbf{P}_{k-1}}\right)]$$

Time equations:

$$\chi_{k|k-1} = f_k(\chi_{k-1}) \quad (17)$$
$$\tilde{x}_k^- = \sum_{i=0}^{2n} W_i^m \chi_{i,k|k-1} \quad (18)$$
$$\mathbf{P}_k^- = \sum_{i=0}^{2n} W_i^c (\chi_{i,k|k-1} - \tilde{x}_k^-)(\chi_{i,k|k-1} - \tilde{x}_k^-)^t + R_w \quad (19)$$
$$y_{k|k-1} = h_k(\chi_{k|k-1}) \quad (20)$$
$$\tilde{y}_k^- = \sum_{i=0}^{2n} W_i^m y_{i,k|k-1} \quad (21)$$

Measurement equations:

$$\mathbf{P}_{y_k y_k} = \sum_{i=0}^{2n} W_i^c (y_{i,k|k-1} - \tilde{y}_k^-)(y_{i,k|k-1} - \tilde{y}_k^-)^t + R_v \quad (22)$$
$$\mathbf{P}_{x_k y_k} = \sum_{i=0}^{2n} W_i^c (\chi_{i,k|k-1} - \tilde{x}_k^-)(y_{i,k|k-1} - \tilde{y}_k^-)^t \quad (23)$$
$$K_k = \mathbf{P}_{x_k y_k} \mathbf{P}_{y_k y_k}^{-1} \quad (24)$$
$$\tilde{x}_k = \tilde{x}_k^- + K_k(y_k - \tilde{y}_k^-) \quad (25)$$
$$\mathbf{P}_k = \mathbf{P}_k^- - K_k \mathbf{P}_{y_k y_k} K_k^t \quad (26)$$

where R_w and R_v are the covariance matrices of process and measurement noise, respectively.

The block diagram representation of the unscented Kalman filter based estimation scheme for the nonlinear quadrotor attitude dynamics is given in Figure 2. Desired state vector x_{ref} and estimated state vector $\tilde{x}$ are fed into the summation block to create error signal e. Input signal u of the quadrotor is calculated in the controller block according to the error input. With input u and process noise w, controller signal is applied to the dynamics of the quadrotor. States of the quadrotor are measured by sensors that are subjected to measurement noise. Then, measured states are passed into the unscented Kalman filter based estimator to estimate and recover the signal $\tilde{x}$ out of noise.

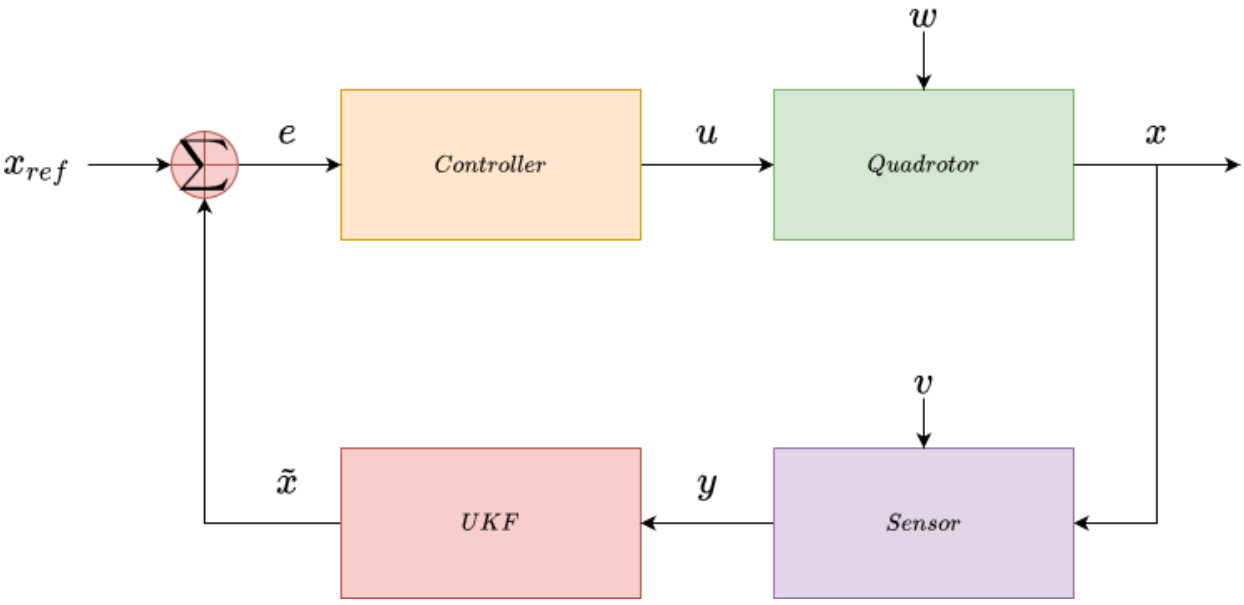


Figure 2. Unscented Kalman filter based estimation scheme of nonlinear quadrotor dynamics

4. RESULTS

The initial condition for the states are chosen as $x_0 = [\phi, \theta, \psi] = [0, 0, 0]$. The variance of the process noise w is 0.01 $[rad^2]$ and the variance of the measurement noise v is 0.02 $[rad^2]$. Time step Δt is 0.1 [s] and simulation time T is 50 [s]. The results of the unscented Kalman filter based estimator are given in Figures 3 – 5 for ϕ, θ and ψ states, where $\{\phi, \theta, \psi\}_{ide}$ are the ideal responses, $\{\phi, \theta, \psi\}_{meas}$ are the measured signals and $\{\phi, \theta, \psi\}_{ukf}$ are the responses of the unscented Kalman filter based estimator, respectively. The comparisons of the estimation error and noise component are given in Figures 6 – 8 for ϕ, θ and ψ states where $\{\phi, \theta, \psi\}_{noi}$ are the total noise and $\{\phi, \theta, \psi\}_{err}^{ukf}$ are the estimation errors of the unscented Kalman filter based estimator. Three different metrics are evaluated to compare the effectiveness of the unscented Kalman filter: variance, mean absolute error and root mean square error. The formulas of the metrics are given in Equations 27 -29.

$$VAR = \frac{1}{N}\sum_{k=1}^{N}(y_k - \bar{y}_k)^2 \qquad (27)$$

$$MAE = \frac{1}{N}\sum_{k=1}^{N}|y_k - \tilde{y}_k| \qquad (28)$$

$$RMSE = \sqrt{\frac{1}{N}\sum_{k=1}^{N}(y_k - \tilde{y}_k)^2} \qquad (29)$$

Numerical results of the estimator for the derived metrics are given in Table 1 where noise represents the total noise component of the measured signal comprise of process and measurement noise, respectively.

Table 1. Numerical results of the unscented Kalman filter

		ϕ	θ	ψ
MAE	Noise	0.1373	0.1335	0.1341
	UKF	0.0461	0.0521	0.0487
$RMSE$	Noise	0.1707	0.1666	0.1675
	UKF	0.0579	0.0672	0.0609
VAR	Noise	0.0292	0.0278	0.0281
	UKF	0.0033	0.0044	0.0037

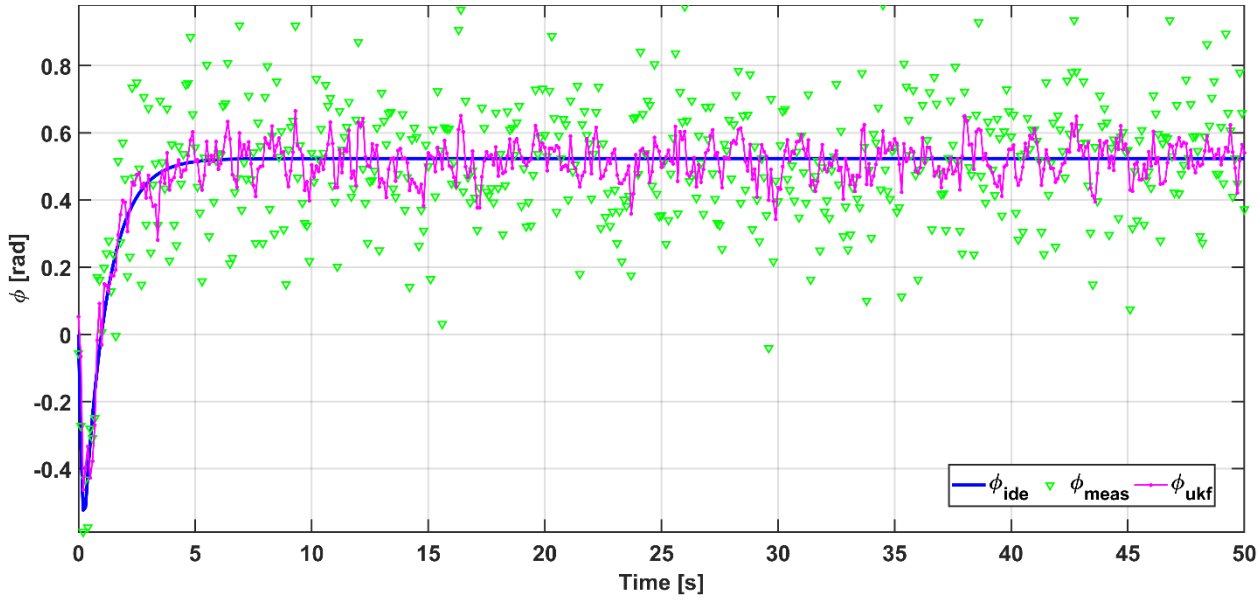


Figure 3. Results of the unscented Kalman filter estimator for ϕ angle

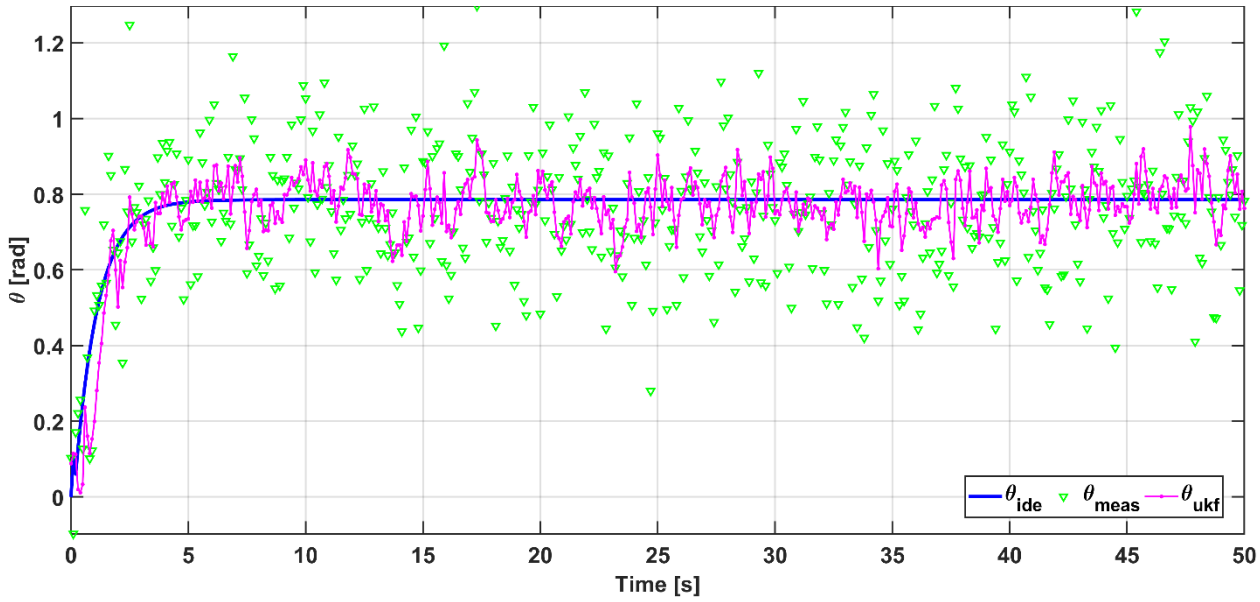


Figure 4. Results of the unscented Kalman filter estimator for θ angle

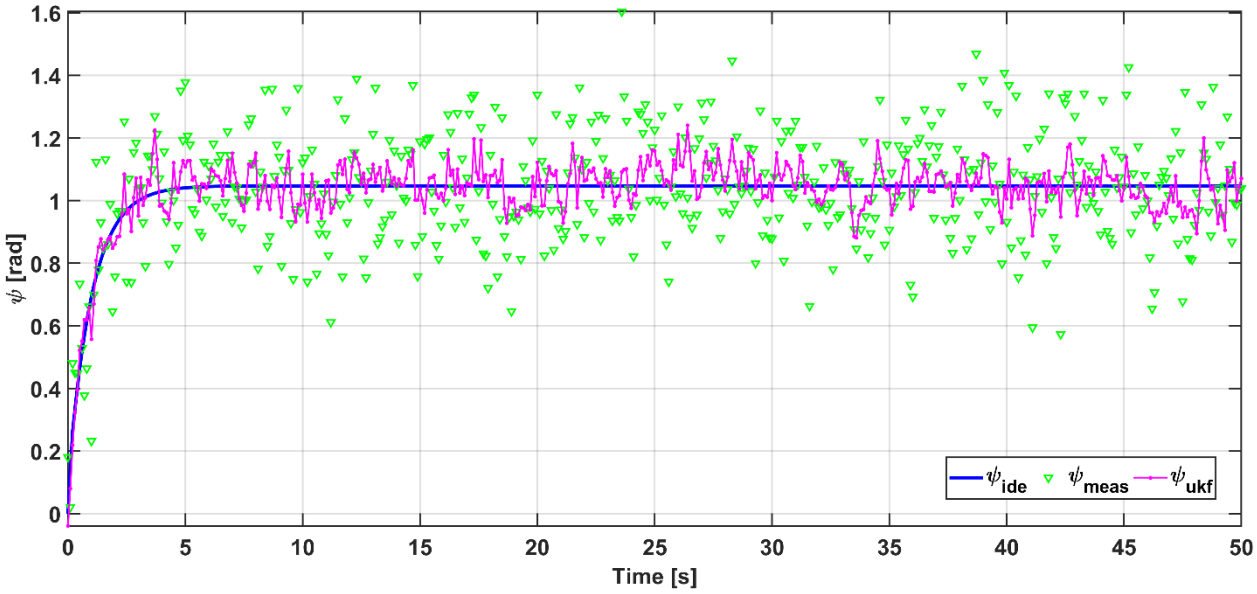


Figure 5. Results of the unscented Kalman filter estimator for ψ angle

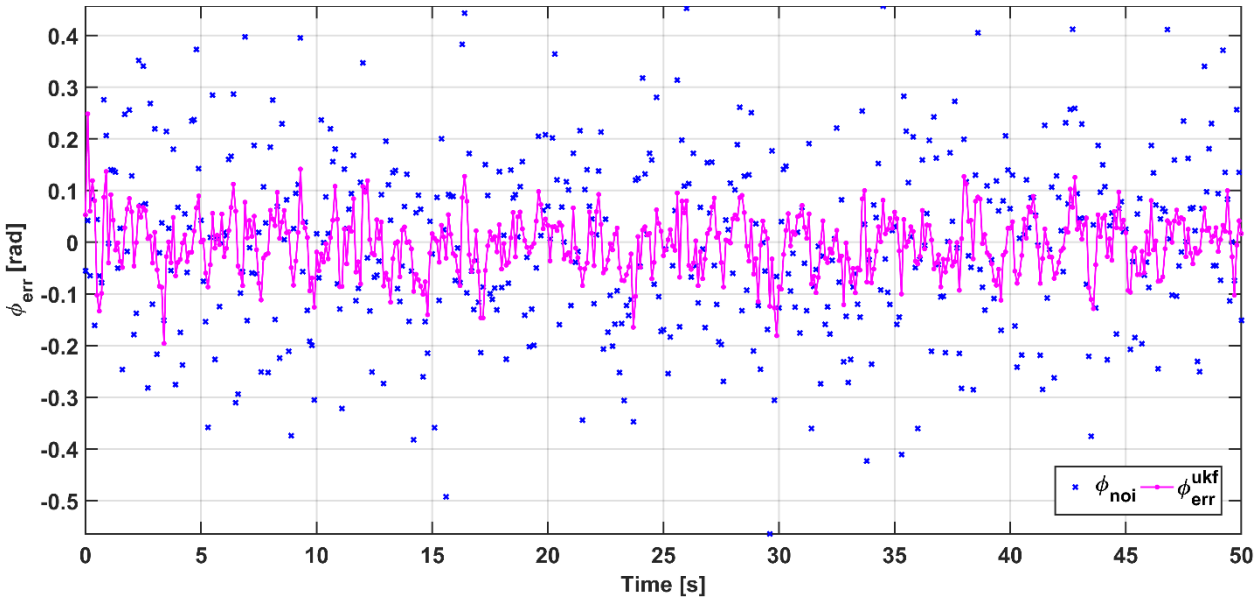


Figure 6. Residuals of the unscented Kalman filter and noise for ϕ angle

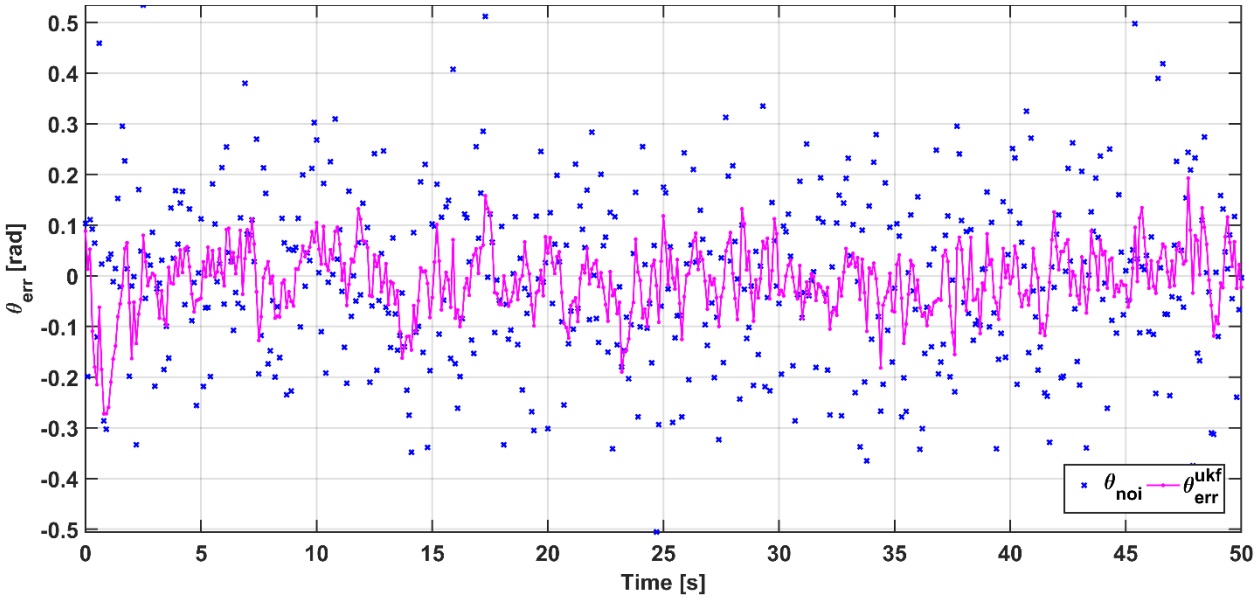


Figure 7. Residuals of the unscented Kalman filter and noise for θ angle

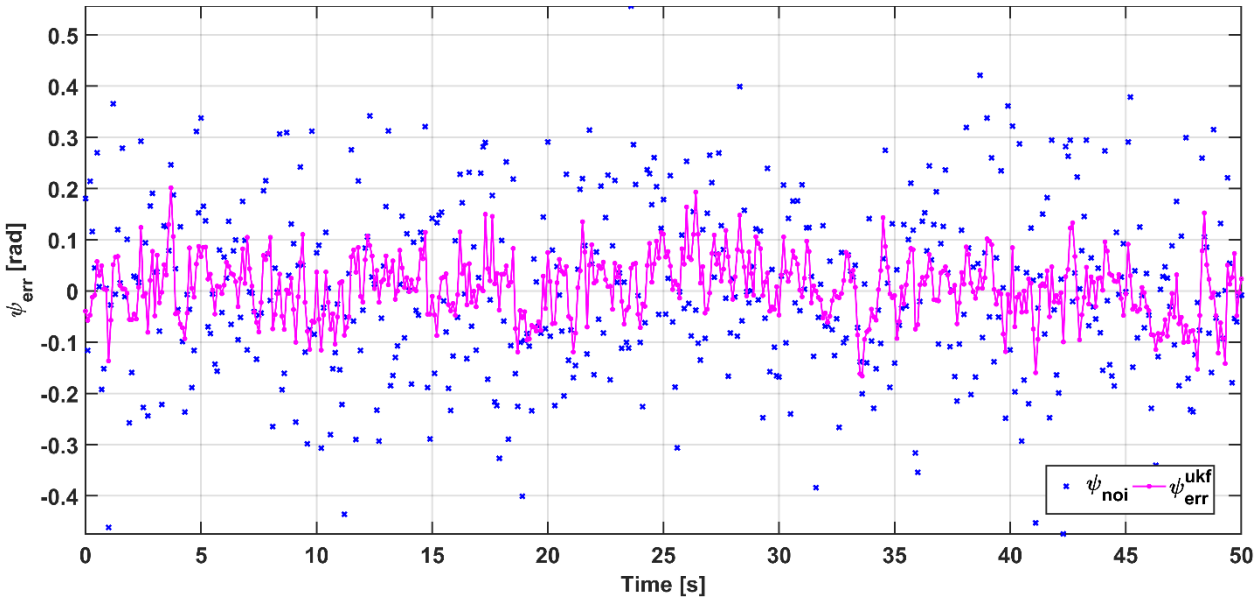


Figure 8. Residuals of the unscented Kalman filter and noise for ψ angle

5. CONCLUSIONS

Unscented Kalman filter based estimation scheme is presented in this study to handle the process and measurement noise that are distributed on the nonlinear quadrotor attitude and sensor dynamics, respectively.

Statistical analysis show that, mean absolute error is reduced from 0.1373 to 0.0461 for ϕ, 0.1335 to 0.0521 for θ and 0.1341 to 0.0487 for ψ, respectively. Root mean square error of the noise is reduced from 0.1707 to 0.0579 for ϕ, 0.1666 to 0.0672 for θ and 0.1675 to 0.0609 for ψ, respectively. Also, variance of the noise is reduced from 0.0292 to 0.0033 for ϕ, 0.0278 to 0.0044 for θ and 0.0281 to 0.037 for ψ, respectively.

In [4], it is reported that the absolute attitude estimation error of the Kalman filter is lower than 0.3 degree. In [10], absolute attitude estimation error of the optimized extended Kalman filter is within 0.0015 degree and in [22], the mean heading estimation error of the unscented Kalman filter is given as 5 degree, respectively. So, it can be said that the results of the nonlinear attitude estimation scheme are coherent with the previous studies.

According to the results, nonlinear estimation scheme is proven to be the effective solution for the considered problem.

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