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*Original Article*

# Unscented Kalman Filter Application for State Estimation of a Qball 2 Quadrotor

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***Abstract*** - *Accurate state estimation is pivotal in controlling quadrotors effectively. For positioning tasks, employing filtering techniques like the Extended Kalman Filter (EKF) and Unscented Kalman Filter (UKF) is common practice. However, the Qball 2 quadrotor poses a challenge due to its highly nonlinear nature, exacerbated by Gauss interference, which can degrade the EKF's accuracy. Consequently, this research centers on evaluating the applicability of the UKF nonlinear filtering method to estimate the Qball 2 quadrotor's state. Utilizing data from gyroscope and Global Positioning System (GPS) measurements, this estimation process incorporates deliberately introduced sensor noise to mimic real-world conditions. Thorough testing across diverse scenarios underscores the UKF filter's superior performance in state estimation for the quadrotor. This paper introduces a significant approach to bolstering the navigation system's precision and dependability for the Qball 2 quadrotor, offering insights into enhancing its overall performance.*

***Keywords*** - *Kalman filter, UKF filter, Measurement noise, Position estimation, Qball 2 quadrotor.*

## 1. Introduction

### *1.1. Introducing the Qball 2 type Quadrotor*

Unmanned Aerial Vehicles (UAVs) have gained popularity due to their straightforward design, cost-effectiveness, and user-friendly nature. This paper explores the examination of a Qball 2 quadrotor, which is propelled by four motorized propellers. Data Acquisition (DAQ) cards are utilized to collect data from the HiQ compartment. Integration between the GPS receiver and the HiQ daughterboard is seamless, facilitated by a GPS serial input labeled ID10.

Additionally, the quadrotor features Real-Time Control Software (QuaRC), allowing researchers to efficiently develop and evaluate controllers through the Matlab/Simulink interface. Controller models created in Simulink can be seamlessly transferred and compiled into executable files on the Gumstix-embedded computer using QuaRC 1.

The system's configuration is visually depicted in Figure 1. Consider the relevant reference frames illustrated in Figure 2, where Oxyz represents the inertial reference frame, and BXYZ is the relative reference frame attached to the quadrotor, corresponding to the fixed frame of the quadrotor. The three rotation angles of the quadrotor around the corresponding axes are denoted as the roll angle $\Phi$, the pitch angle $\theta$, and the yaw angle $\Psi$. Furthermore, $F_1$, $F_2$, $F_3$, and $F_4$ represent the thrust generated by the four propellers.

### *1.2. Introduction to Kalman Filters*

The estimation algorithm for nonlinear equation systems utilized in positioning has been the subject of extensive research for decades. In 1960, Kalman introduced the Kalman filtering algorithm, primarily designed for linear equations with a Gaussian noise distribution. However, the prevalent equations in positioning are predominantly nonlinear, rendering the Kalman filtering technique impractical.

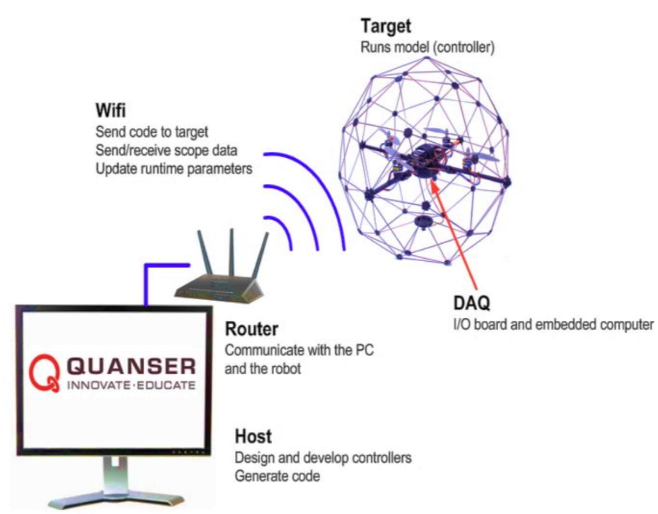



**Fig. 1 Configuration of the Qball 2 type quadrotor**

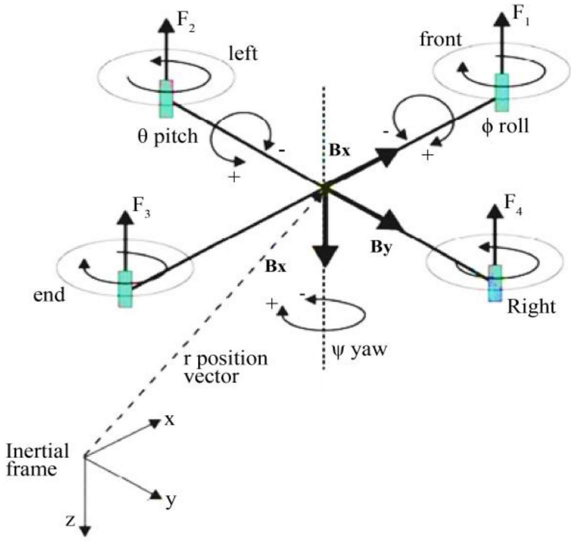



**Fig. 2 Quadrotor reference frames**

To address this challenge, Anderson and Moore devised an enhanced method in 1979, termed the Extended Kalman Filter (EKF), as an extension of Kalman's original algorithm. Nevertheless, EKF necessitates linearization for nonlinear equations, which may result in reduced accuracy, particularly with highly nonlinear equations.

In response to this limitation, Julier and Uhlmann proposed the Unscented Kalman Filter (UKF) in 1997, which obviates the need for linearization steps. The UKF demonstrates comparable accuracy to the EKF, particularly when incorporating second-order coefficients in the Taylor expansion.

The following papers introduce the UKF non-linear Kalman filtration method and some of its applications: The paper [2] introduced the UKF method for estimating the state of non-linear systems. The paper points out the limitations of the EKF method and proposes a new method based on the use of sample points to approximate the probability distribution of the state. The paper also compares the effectiveness of UKF and EKF.

The paper [3] gave an overview of the UKF method and its applications in various fields, such as control, positioning, and identification. The paper also covers UKF variants, such as square-root UKF, divided difference UKF, and central difference UKF.

The paper [4] delves into the study of the application of UKF to the estimation of both states and parameters of non-linear systems. The paper proposes a method called dual estimation, which combines UKF and expectation maximization algorithms. The paper also illustrates the results of this method for estimating the state of a pendulum. The paper [5] delves into the application of the UKF for estimating the dynamic states of power systems. It argues that the application of UKF holds the potential to effectively address challenges posed by non-linearity, latency, and interference within power systems.

The paper [6] explored a variant of the UKF known as the square-root UKF. This method employs Cholesky analysis to calculate sample points, offering advantages such as minimizing rounding errors and enhancing the overall stability of the UKF.

The paper [7] delves into a novel method, the unscented transformation, designed for transforming non-linear probability distributions. This method serves as the foundational concept for the UKF filter and finds applications in various filtering and estimation problems.

The paper [8] explored the application of UKF to address probabilistic inference problems in dynamic-state space models. It introduces a method known as the sigma-point Kalman filter, which combines elements of UKF and particle filters. The paper provides illustrative results from applying this method to estimate the state of a mobile robot. Additionally, it showcases the significance of the method in training a Hidden Markov Model (HMM).

The paper [9] delves into the application of the sigma-point Kalman filter to state estimation problems and sensor fusion to non-linear systems such as cars.

The paper [10] delves into the application of UKF to Simultaneous Localization And Mapping (SLAM) on a drone. The paper uses a dynamical model based on quaternion to represent the state of the drone and uses an image sensor to collect features of the environment.

As such, papers [2] to [11] share the commonality of focusing on the UKF method and its applications to non-linear systems. However, these papers do not yet include content on the application of UKF to the estimation of the state of a Qball 2 quadrotor.

In this paper, the author proposes the utilization of the UKF method to accurately and stably estimate the state of the Qball 2, a type of quadrotor known for its unique features and compatibility with various sensor types. The novelty and creativity of the study lie in the author's demonstration that the application of the UKF method can yield accurate and stable state estimates, even in the presence of measurement noise affecting GPS sensors and gyroscopes.

## 2. Model of the Qball 2 quadrotor

### *2.1. Equations of Motion*

The Qball 2 Quadrotor is a simple-structured drone with the features of four motors mounted in a cross-shaped structure, each equipped with a propeller. The 'front-rear' propeller rotates counterclockwise while the 'right-left' propeller rotates clockwise. This configuration is essential for ensuring the stable operation of the quadrotor [1], as it helps in achieving balanced lift and control.

$$F_i = K_f \omega_i^2 \tag{1}$$

The thrust *($F_i$)* generated by each propeller is determined by the thrust coefficient *($K_f$)* and the angular velocity of the propeller *($\omega_i$)*. *I*n addition to upward thrust, each rotating propeller produces torque calculated by the formula:

$$M_i = K_m \omega_i^2 \tag{2}$$

Where $M_i$ is the moment generated by each blade along the z-axis, and $K_m$ is the drag coefficient.

To find the dynamic equations of the system, start with the expression for calculating the total thrust of the four blades:

$$F_\Sigma = K_f(\omega_1^2 + \omega_2^2 + \omega_3^2 + \omega_4^2) \tag{3}$$

The linear acceleration equations are described as follows:

$$\begin{bmatrix}\ddot{x}\\ \ddot{y}\\ \ddot{z}\end{bmatrix} = \begin{bmatrix}0\\0\\-g\end{bmatrix} + \frac{R}{m}\begin{bmatrix}0\\0\\F_\Sigma\end{bmatrix}; R = R_z(\psi)R_y(\theta)R_x(\phi) \tag{4}$$

Where $R$ is the rotation matrix from the coordinate system attached to the earth to the corresponding coordinate system according to the axes of the quadrotor. The force moments along the corresponding axes are as follows:

$$\begin{cases}\tau_x = \frac{LK_f}{\sqrt{2}}(\omega_1^2 + \omega_2^2 - \omega_3^2 - \omega_4^2)\\ \tau_y = \frac{LK_f}{\sqrt{2}}(-\omega_1^2 + \omega_2^2 + \omega_3^2 - \omega_4^2)\\ \tau_z = K_m(\omega_1^2 - \omega_2^2 + \omega_3^2 - \omega_4^2)\end{cases} \tag{5}$$

The Euler equation describes the angular acceleration associated with the quadrotor within the dynamic model. This equation is formulated as follows:

$$\begin{bmatrix}\ddot{\phi}\\ \ddot{\theta}\\ \ddot{\psi}\end{bmatrix} = I^{-1}\left(\begin{bmatrix}\tau_x\\ \tau_y\\ \tau_z\end{bmatrix} - \omega \times I\omega\right);$$
$$I = \begin{bmatrix}I_{xx} & 0 & 0\\ 0 & I_{yy} & 0\\ 0 & 0 & I_{zz}\end{bmatrix}; \tag{6}$$
$$\omega = \begin{bmatrix}\dot{\phi}\\ \dot{\theta}\\ \dot{\psi}\end{bmatrix}$$

From the above relationships, the equations of motion are written as follows:

$$\begin{cases}\ddot{x} = \frac{F_\Sigma(cos(\phi)\,sin(\theta)\,cos(\psi) + sin(\phi)\,sin(\psi))}{M}\\ \ddot{y} = \frac{F_\Sigma(cos(\phi)\,sin(\theta)\,sin(\psi) - sin(\phi)\,cos(\psi))}{M}\\ \ddot{z} = \frac{F_\Sigma(cos(\phi)\,cos(\theta))}{M} - 9.81\\ \ddot{\phi} = \frac{\tau_x + (I_{yy} - I_{zz})\dot{\theta}\dot{\psi}}{I_{xx}}\\ \ddot{\theta} = \frac{\tau_y + (I_{zz} - I_{xx})\dot{\phi}\dot{\psi}}{I_{yy}}\\ \ddot{\psi} = \frac{\tau_z + (I_{xx} - I_{yy})\dot{\theta}\dot{\phi}}{I_{zz}}\end{cases} \tag{7}$$

Based on the input angular velocity of the rotor, it is possible to derive the continuous state of the quadrotor, including position and direction, according to the input angular velocity of the rotor, thrust force, and force moment around the corresponding axes. The position and direction, measurable using a GPS device, are continuous states of the quadrotor. On the other hand, the force moment around the corresponding axes cannot be physically measured and requires estimation. GPS measurements, while providing valuable data, are subject to noise, rendering them non-absolute.

The continuous-time state-space model of the Qball 2 is as follows:

$$\dot{X} = f_x(X, u) + n \tag{8}$$

Where $u$ is the input vector, $X$ is the state vector of the system, $f_x(X,u)$ is the nonlinear function matrix, and $n$ is the process noise or input noise.

$$\begin{cases}X = [x \quad y \quad z \quad \phi \quad \theta \quad \psi \quad \dot{x} \quad \dot{y} \quad \dot{z} \quad \dot{\phi} \quad \dot{\theta} \quad \dot{\psi}]\\ u = [F_\Sigma \quad \tau_x \quad \tau_y \quad \tau_z]\end{cases} \tag{9}$$

The process noise or input noise is $n \sim N(\bar{x}, \sigma_\omega)$, assumed to be Gaussian distributed with a mean of $\bar{x} = 0$ and a variance of $\sigma_\omega = 1e - 6$.

### *2.2. Model of the Sensor*

GPS measurement sensor to measure the position of the quadrotor in a spherical coordinate system. GPS sensors have the following mathematical model:

$$y_k^{GPS} = r(kT_s) + n_k^{GPS} \tag{10}$$

In there,

$y_k^{GPS}$ is the GPS measurement.

$r(kT_s)$ is the actual position of the quadrotor in spherical coordinates.

$n_k^{GPS}$ is the measurement noise with a Gaussian distribution of $n_k^{GPS} \sim N(0, \sigma_{GPS})$ with a standard deviation of $\sigma_{GPS}$. A gyroscope to measure angular velocity in a coordinate system attached to the quadrotor. The gyroscope has the following mathematical model:

$$y_k^{Gyro} = \dot{\Omega}(kT_s) + n_k^{Gyro} \tag{11}$$

In there,

$y_k^{Gyro}$ is the gyroscope measurement.

$\dot{\Omega}(kT_s)$ is the actual angular velocity of the quadrotor.

$n_k^{Gyro}$ is the measurement noise with a Gaussian distribution of $n_k^{Gyro} \sim N(0, \sigma_{Gyro})$ with a standard deviation of $\sigma_{Gyro}$.

## 3. Applying the UKF algorithm to Qball 2

The UKF filter stands out in scenarios involving non-linear models, as it does not necessitate assumptions regarding the linearity of the system or measurement model. Its robustness extends to situations where derivative conditions are unstable, or measurement errors are substantial.

Consequently, the UKF filter is commonly employed for estimating the state of systems characterized by uncertain models or non-linear measurements. This study's primary aim is to utilize the UKF filter to estimate the position of the Qball 2 quadrotor accurately. This entails addressing the inherent noise in GPS measurements and deducing orientation values that cannot be directly observed. Leveraging the UKF filter is essential for achieving precise and stable estimates amidst measurement uncertainties and non-linearities.

The Unscented Kalman Filter utilizes a deterministic sampling approach to effectively represent the probability distribution of a state by employing a carefully selected set of sigma points. These sigma points are strategically chosen to preserve the mean and covariance of the probability distribution faithfully. Subsequently, they transform the nonlinear function, yielding new points that reflect the probability distribution of the subsequent state. Ultimately, the mean and covariance of the updated probability distribution are computed by applying weighted values to the sample points.

In this paper, the UKF was chosen to filter sensor measurements, playing a pivotal role in estimating the quadrotor's state. Given the noise inherent in GPS measurements, filtering out this noise is crucial. Since directly measuring the quadcopter's orientation is unfeasible, it becomes an unobservable state within the system. The UKF effectively estimates this unobservable state based on gyroscope measurements, thereby filtering out noise and enhancing the accuracy of the estimation process.

Time update:

$$x^{(i)} = \hat{x}^{(+)} + \tilde{x}^{(i)}$$

$$x_{k+1}^{(i)} = f(x^{(i)}, u_k)$$

$$\hat{x}_{k+1}^{(-)} = \frac{1}{2n}\sum_{i=1}^{2n} x_{k+1}^{(i)}$$

$$P_{k+1}^{(-)} = \frac{1}{2n}\sum_{i=1}^{2n}\left(x_{k+1}^{(i)} - \hat{x}_{k+1}^{(-)}\right)\left(x_{k+1}^{(i)} - \hat{x}_{k+1}^{(-)}\right)^T + Q \quad (12)$$

Measurement update:

$$\bar{Y} = \frac{1}{2n}\sum_{i=1}^{2n} Y^{(i)}$$

$$P_{xy} = \frac{1}{2n}\sum_{i=1}^{2n}\left(x_k^{(i)} - \hat{x}_k^{(-)}\right)\left(Y^{(i)} - \bar{Y}\right)^T$$

$$P_y = \frac{1}{2n}\sum_{i=1}^{2n}\left(Y^{(i)} - \bar{Y}\right)\left(Y^{(i)} - \bar{Y}\right)^T + R \quad (13)$$

$$K = P_{xy}P_y^{-1}$$

$$x_k^{(+)} = \hat{x}_k^{(-)} + K(Y_k - \bar{Y})$$

$$P_k^{(+)} = P_k^{(-)} - KP_{xy}^T \quad (14)$$

Thus, UKF's main implementation steps in the Matlab program can be summarized as follows:

- Step 1: Select a set of sample points from the probability distribution of the current state.

```
M = chol(P_k1,'upper');
xBar_i_p = sqrt(n)*[M -M];
xI_p = x_k0 + xBar_i_p;
```

In there,

M is the Cholesky matrix of the covariance matrix P_k1.

xBar_i_p is the set of sample points generated from the Cholesky matrix.

xI_p is the set of new sample points.

- Step 2: Pass each sample point through the nonlinear function of the dynamic system, obtaining a set of new sample points belonging to the probability distribution of the next state.

```
for i = 1:(2*n)
x_ki(:,i) = simout_Temp.simout.Data(end,:)';
end
```

In it, each sample point from xI_p is passed through the system model to obtain x_ki, a set of new sample points belonging to the probability distribution of the next state.

- Step 3: Calculate the weights for the sample points.

```
xCap_Minus = (1/(2*n))*sum(x_ki,2);
```

where xCap_Minus is the average value of the set of sample points.

- Step 4: Calculate the mean and covariance of the probability distribution of the next state using the weights and new sample points.

```
PMinus = zeros(12);
for i = 1:(2*n)
PMinus=PMinus+(x_ki(:,i)-xCap_Minus)*(x_ki(:,i)-
xCap_Minus)' +Q;
end
PMinus = (1/(2*n)).*PMinus;
```

Where PMinus is the covariance matrix of the next state.

- Step 5: Update the mean and covariance of the probability distribution of the next state using measured observations and Kalman-Gain formulas.

```
M = chol(PMinus,'upper');
xBar_i = sqrt(n)*[M -M];
```

```
xI_p = xCap_Minus + xBar_i;
for i = 1:(2*n)
yMeasure(:,i)= simout_Temp.sensorMeasure.Data(end,:)';
end
yBar = (1/(2*n))*sum(yMeasure,2);
Pxy = zeros(12,6);
Py = zeros(6);
for i = 1:(2*n)
Pxy=Pxy+(xI_p(:,i)-xCap_Minus)*(yMeasure(:,i)-yBar)';
Py = Py + (yMeasure(:,i)-yBar)*(yMeasure(:,i)-yBar)' + R;
end
Pxy = (1/(2*n)).*Pxy;
Py = (1/(2*n)).*Py;
K = Pxy*inv(Py);
xCap = xCap_Minus + K*(yMeasurement(:,count) - yBar);
P_k = PMinus - K*Pxy';
```

In there,
xBar_i is the set of new sample points belonging to the probability distribution of the next state.
yBar is the average value of the set of measurements.
Pxy and Py are covariance matrices related to the correlation between state and measurement.
K is the Kalman-Gain matrix.
xCap and P_k are the mean and covariance of the probability distribution of the next state after obtaining measurement data.

## 4. Results and Discussions

The Qball 2 quadrotor was modeled in Simulink with the parameters shown in Table 1 and simulated for 2.5 seconds with a time step. $T_s = 0.1(s)$. Utilizing the UKF filter, we undertake the estimation of both the position (x, y, z) and angular (roll Φ, pitch θ, yaw Ψ) coordinates, with the resultant data being visually presented in Figures 3 and 4. Each of these figures portrays the actual state of the quadrotor's position and angular coordinates through the representation of a red line. Conversely, in the absence of employing a UKF filter, the observed state of the quadrotor exhibits notable fluctuations, evident from the oscillations along the blue line.

**Table 1. System variables**

| Parameter | Symbol | Value | Unit |
|---|---|---|---|
| Mass | M | 1,4 | kg |
| Moments of inertia about the x, y, and z axes | $I_{xx}$, $I_{yy}$, $I_{zz}$ | 0,03 | Kg.m$^2$ |
| The distance between the propeller and the center of gravity | L | 0,2 | m |
| Thrust factor | $K_f$ | 0,1 | |
| Drag factor | $K_m$ | 0,1 | |
| Angular velocity of the propeller: the angular velocity of each propeller | $\omega_i$ i = 1÷4 | 2,8; 3,2; 3,2; 2,8 | rad/s |
| The standard deviation of GPS measurement noise | $\sigma_{GPS}$ | 0,54 | m |
| The standard deviation of the measurement noise from the gyroscope | $\sigma_{Gyro}$ | 0,15 | radian |

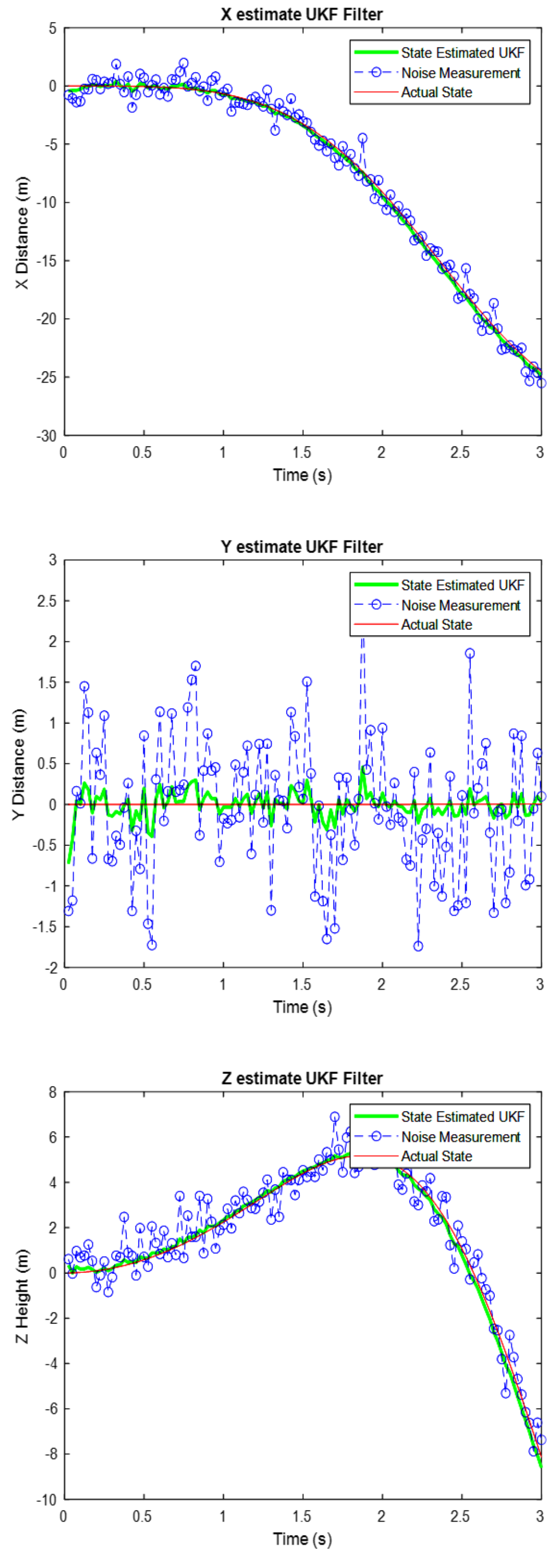
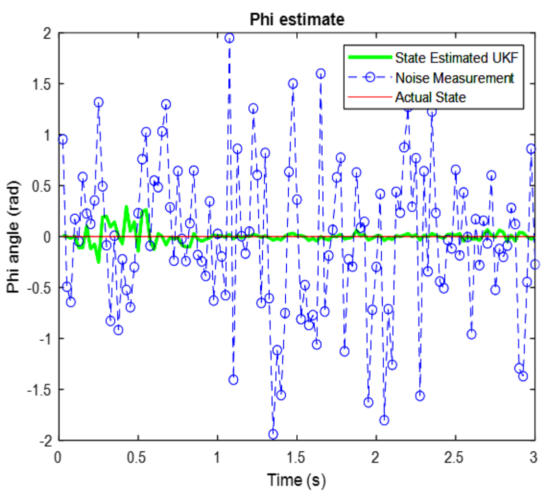
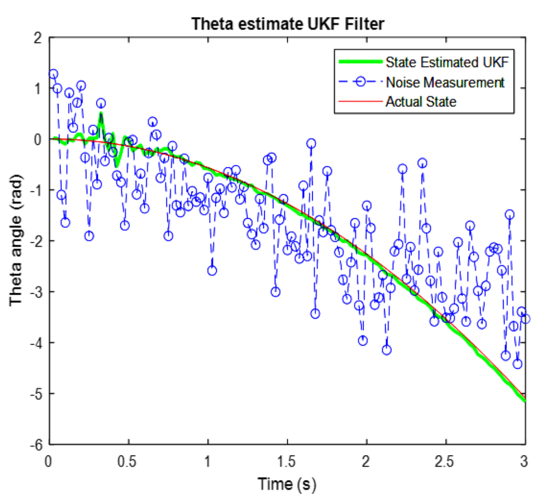



**Fig. 3 The position coordinates obtained from UKF implementation.**

Such fluctuations predominantly stem from the presence of measurement noise, particularly impacting the accuracy of the GPS sensor and gyroscope readings. Nevertheless, upon incorporating the UKF filter into the estimation process, a considerable reduction in the adverse effects of measurement noise on both the GPS sensor and gyroscope is observed. Consequently, the trajectory followed by the estimated state of the quadrotor appears significantly smoother, as depicted by the trajectory along the black line. Ultimately, this trajectory converges closer to the actual state of the quadrotor, as represented by the red line. Furthermore, an in-depth examination of the angular coordinate state graphs accentuates the UKF's remarkable efficacy in accurately predicting the quadrotor's angular states. This attribute of the UKF proves to be particularly advantageous in scenarios where non-linearity is more pronounced, especially in the context of measuring angular coordinates. Consequently, the UKF emerges as a fitting solution for addressing the inherent complexities encountered in nonlinear systems. By ensuring stable and high-quality operational performance, the incorporation of the UKF filter significantly enhances the quadrotor's reliability, particularly in scenarios characterized by the presence of measurement noise affecting the GPS sensor and gyroscope readings.



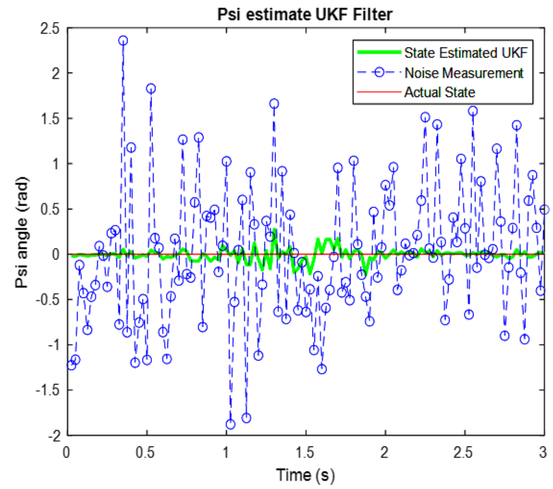




**Fig. 4 The angular coordinates obtained from UKF implementation.**

## 5. Conclusion

This study focuses on applying the UKF filter to estimate the state of the Qball 2 quadrotor during control. The UKF effectively addresses challenges posed by the highly nonlinear nature of the Qball 2 and the impact of measurement noise on GPS sensors and gyroscopes. During the estimation of position and angular coordinates, the UKF not only reduces quadrotor state oscillation caused by measurement noise but also nearly eliminates it. As a result, there is stable convergence between the measured and actual states, particularly under non-linear conditions and the influence of measurement noise from GPS sensors and gyroscopes. In addition, the analysis of the angular coordinate state graph showcases the prowess of UKF in predicting quadrotor angular states, particularly in highly nonlinear environments. This underscores the effectiveness of UKF as a powerful tool for state estimation in nonlinear and complex systems such as quadrotors.

In conclusion, this study not only offers an effective state estimation method for the Qball 2 quadrotor but also paves the way for significant applications of the UKF in non-linear control systems. This has the potential to enhance the reliability and accuracy of navigation systems in practical quadrotor applications.

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