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# Attitude Estimation by using Unscented Kalman Filter with Constraint State

Vichetra Yi [1*], Sarot Srang [1], Chivorn Keo [1]

[1] *Department of Industrial and Mechanical Engineering, Dynamics and Control Laboratory, Institute of Technology of Cambodia, Russian Federation Blvd., P.O. Box 86, Phnom Penh, Cambodia*

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**Abstract:** *Quadcopters or quadrotors have always desired to fly smoothly and stay on their path in order to enhance their application. This better performance can be achieved depending on the accuracy of the data. However, relying purely on sensor data cannot be accepted due to the inaccuracy of measurement, thus state estimation to filter noise out is important. This paper is focused on performance evaluation on quadrotors attitude estimation using Unscented Kalman filter (UKF) by comparison with quadrotors attitude computed from the mathematical model. The UKF is an algorithm dealing with noise filters that can be used for state estimation such as attitude and bias of sensors. UKF is divided into two steps which are Measurement Update, and Time Update. However, the algorithm is initialized by determining initially on the mean and the covariance. Then, the measurement update algorithm uses the accelerometer sensor data and magnetometer sensor data pose the next time update. Gaussian with covariance (Q and R) of the UKF algorithm are determined in this paper. Quaternion is used to describe state equations which are based on the kinematic model. The input of the state equation is taken from sensors of the Pixhawk 4 controller which are gyro meters (data of angular velocity). In addition, the output equation is based on accelerometer modeling and magnetometer modeling including data from accelerometer sensors and magnetometer in the Pixhawk 4 controller. MATLAB & Simulink have been used for this experiment and Pixhawk Controller hardware is used as the flight controller. The result of attitude estimation expressed about component of quaternions and bias of sensor from Pixhawk 4. The graph is shown the performance of attitude quadrotors and bias of sensor.*

**Keywords:** UAV; Unscented Kalman filter; Estimation; Accelerometer; Mathematical modeling

## 1. INTRODUCTION

Application quadrotor of remote sensing, direct geo-referencing and 3-D mapping [1] or constructing large image mosaics [2] and a key requirement is information of high-fidelity aircraft attitude. Moreover, the application of airborne target tracking, noted that error is most sensitive to attitude uncertainty [3]. In recent years, low-cost inertial measurement units (IMUs) have been made by advances in micro-electro-mechanical systems (MEMS). However, these components have limited accuracy which does not make them adequate alone due to the accumulation of the sensor biases over time [4]. The high accuracy of the Global Positioning System is important. Velocity measurement from GPS has also led the researcher to develop a single GPS antenna-based attitude solution. A GPS receiver has well-known benefits and the functional integration of a low-cost Inertial Navigation System (INS) [5].The development of several GPS/INS formulations that vary in terms of the number of navigation states estimated [6] and the form of GPS information used for measurement updates [7].

State estimation as a means of checking instrument accuracy and data consistency is now used by many flight-test groups. Once a consistently smoothed set of time histories is obtained from the data, other analyses such as identification of stability and control derivative are readily performed. In fact, a relatively simple routine may be used for identification tasks, allowing the analyst freedom to develop a proper aerodynamic model. Since the data consistency had been extensively treated in the literature, it will not be discussed further here [8]. Instead, we will estimate the state of the aircraft that can measure from the sensor.

The first flight of the experiment, the manual control mode, has been used to fly the quadrotors for the purpose of gathering

* Corresponding author: Vichetra Yi
*E-mail: vichetra_vi@gsc.itc.edu.kh; Tel: +855-81 499 114*

sensor data such as three attitude angles [9].These data then would be used to be a case study for autonomous control loop design. The obtained signals or data from the sensors have a lot of vibrations due to the mechanical nature of the system and noise with bias due to the sensors themselves and environmental effects which as to be filtered to obtain their accuracy. The common solution in the literature is to use a kind of Kalman filter.

The Unscented Kalman Filter (UKF), a member of the Linear Regression Kalman Filter family, attempts to remove some of the short-comings of the EKF in the estimation of nonlinear systems. The UKF is an extension of the traditional Kalman Filter for the estimation of nonlinear systems that implements the unscented transformation. The unscented transformation uses a set of samples, or sigma points that are determined from the a priori mean and covariance of the state. The sigma points undergo a nonlinear transformation. The posterior mean and covariance of the state are determined from the transformed sigma points [10].This approach gives the UKF better convergence characteristics and greater accuracy than the EKF for nonlinear systems [11].

This research topic is a specific problem noticed in the development of small prototypes of quadrotors which include sensors and hardware boards for purpose of experimentation. The onboard hardware and software have been designed for these quadrotors where the hardware includes an IMU that contains three-axis accelerometers, gyro meters, and magnetometers. The system is light and small enough to fly on quadrotors.

This paper is organized into 4 sections. Kinematic modelling of attitude, modeling of sensors, and UKF algorithm are described in section 2. The result and discussion are shown in section 3. And section 4 is the conclusion.

## 2. METHODOLOGY

### *2.1 Attitude modeling*

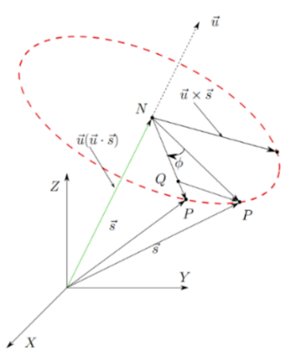


**Fig. 1.** Vector diagram for derivation of rotation formular

Let$\{A\}$ denoted by $\{\vec{x},\vec{y},\vec{z}\}$ be the three coordinates axis unit vectors without a frame of reference. The attitude of the quadrotors has been described in the quaternion component. Rotation quaternion is derived based on the rotation formula as shown in Fig. 1.

The initial position $\vec{s}$ of the vector $\overrightarrow{OP}$ and the final position $\vec{s'}$ is denoted by $\overrightarrow{OP'}$. The unit vector along the orientational axis is denoted by $\vec{u}$. Vector $\vec{s}$ can be expressed as the sum of three vectors:

$$\vec{s} = \overrightarrow{ON} + \overrightarrow{NQ} + \overrightarrow{QP}\,. \tag{Eq. 1}$$

By $\vec{u}\cdot\vec{s}$ is the direct distance between points $O$ and $P$, so the vector $\overrightarrow{ON}$ can be written as follows:

$$\overrightarrow{ON} = \vec{u}(\vec{u}\cdot\vec{s'}), \tag{Eq. 2}$$

$\overrightarrow{NP'}$ can also be described as follow:

$$\overrightarrow{NP'} = \vec{s'} - \overrightarrow{ON} = \vec{s'} - \vec{u}(\vec{u}\cdot\vec{s'}), \tag{Eq. 3}$$

Therefore,

$$\overrightarrow{NQ} = [\vec{s'} - \vec{u}(\vec{u}\cdot\vec{s'})]cos\phi, \tag{Eq. 4}$$

Magnitude of vector $\overrightarrow{NP'}$ is the same as that of vector $\overrightarrow{NP}$ and $\vec{u}\cdot\vec{s'}$. Thus, $\overrightarrow{QP}$ can be expressed as

$$\overrightarrow{QP} = (\vec{u}\cdot\vec{s'})sin\phi\,. \tag{Eq. 5}$$

Following Eq. 2, Eq. 3, and Eq. 4 combine into Eq. 1, together with a slight rearrangement of terms, leads to the rotation formula:

$$\vec{s} = \vec{s'}cos\phi + \vec{u}(\vec{u}\cdot\vec{s'})(1-cos\phi) + \vec{u}\times\vec{s'}sin\phi \tag{Eq. 6}$$

Through the standard trigonometric relationships

$$\begin{aligned} cos\phi &= 2cos^2\frac{\phi}{2} - 1 \\ sin\phi &= 2sin\frac{\phi}{2}cos\frac{\phi}{2} \\ 1 - cos\phi &= 2sin^2\frac{\phi}{2}. \end{aligned} \tag{Eq. 7}$$

And the new quantities

$$\begin{aligned} e_0 &= cos\frac{\phi}{2} \\ e &= \vec{u}sin\frac{\phi}{2}, \end{aligned} \tag{Eq. 8}$$

Let $e_0 = q_0$, $e = [q_1, q_2, q_3]$, and $q = [e;\ e_0]^T$ are components of the quaternions.

Based on Eq. 6 can be derived in a more useful for rotation quaternion form:

$$\vec{s} = (2e_0^2 - 1)\vec{s'} + 2e\left(e^T\vec{s'}\right) + 2e_0\vec{e} \times \vec{s'}.$$

Algebraic representation

$$s = [(2e_0^2 - 1)I + 2ee^T + 2e_0\tilde{e}]s'.$$

Where $I$ is the identity matrix and $\tilde{e}$ is a skew-symmetric matrix

$$\tilde{e} = \begin{bmatrix} 0 & -e_3 & e_2 \\ e_3 & 0 & -e_1 \\ -e_2 & e_1 & 0 \end{bmatrix}.$$

Finally, we can denote the transformation matrix from the component of the quaternion

$$R = (2e_0^2 - 1)I + 2ee^T + 2e_0\tilde{e}. \tag{Eq. 9}$$

Attitude of quadrotors is used in the quaternion component, then we can derive state equations from Eq. 8

$$\dot{q} = \Omega(\omega)q,$$

The propagated quaternion is found from the discrete time

$$q_k = \Omega(\omega_{k-1})q_{k-1}, \tag{Eq. 10}$$

By $\Omega(\omega_{k-1})$ can be computed

$$= \begin{bmatrix} \cos(0.5\|\omega_{k-1}\|\Delta t)\, I - [\tilde{\psi}_{k-1}] & \psi_{k-1} \\ -\psi^T{}_{k-1} & \cos\,(0.5\|\omega_{k-1}\|\Delta t \end{bmatrix}.$$

Where $\psi_{k-1} = \sin(0.5\|\omega_{k-1}\|\Delta t)\,\omega_{k-1}/\|\omega_{k-1}\|$ , $\omega_{k-1}$ is a component of angular velocity that be measured from a gyro meter and $\Delta t$ is the sampling time.

In general, IMU sensors usually have a bias if we ignore the sensor-based MEMS. So, sensor fusion needs to estimate bias for the correct attitude estimate. We can be expressed by:

Let $b_a$ is bias from accelerometer and assumption as a random walk (RW):

$$b_{a(k)} = b_{a(k-1)} + \eta_2\ , \tag{Eq. 11}$$

Let $b_\omega$ is biased from gyro meter and $b_{mag}$ is bias from the magnetometer and assumptions as constant:

$$b_{\omega(k)} = b_{\omega(k-1)} + \eta_3$$

$$b_{mag(k)} = b_{mag(k-1)} + \eta_4, \tag{Eq. 12}$$

Therefore, following Eq. 10, Eq. 11, and Eq. 12, we can rewrite the state equation including bias from the sensor:

$$\begin{bmatrix} q_k \\ b_{a(k)} \\ b_{\omega(k)} \\ b_{mag(k)} \end{bmatrix} = \begin{bmatrix} \Omega(\omega)q_{k-1} + \eta_1 \\ b_{a(k-1)} + \eta_2 \\ b_{\omega(k-1)} + \eta_3 \\ b_{mag(k-1)} + \eta_4 \end{bmatrix}.$$

Where $[\eta_1, \eta_2, \eta_3, \eta_4]^T$ is noise.
$q = [q_0, q_1, q_2, q_3]^T$ is a component of the quaternion

*2.2 Measurement equation*

In this section, we will describe the output equation or measurement equation for applying an Unscented Kalman filter.

Acceleration has been measured by an accelerometer sensor in the body frame (in a step-down IMU configuration). Due to the equation of accelerometer is modeling in body frame:

$$a_{imu} = R^T(\dot{v} - g\vec{z}) + b_a + \eta_a. \tag{Eq. 14}$$

Where $b_a$ is bias term, $\eta_a$ denotes additive measurement noise, and $\dot{v}$ is acceleration in the initial frame. Here, the notation $\vec{z}$ can be dealt with the algebraic expressions of coordinate axes throughout this section. Moreover, high vibration and mounted on a quadrotor have appeared from the accelerometer, so we require significant low-pass mechanical and/or electrical filtering to be usable. Most quadrotor avionics will incorporate an analog antialiasing filter on a MEMS accelerometer before the signal is sampled.

Magnetometers provide the measurement of the ambient magnetic field

$$m_{imu} = R^T Ma + b_m + \eta_m. \tag{Eq. 15}$$

Where $b_m$ is bias in a body fixed frame expression for local magnetic disturbance, $Ma$ is the magnetic field vector expressed in the inertial frame, $\eta_m$ is usually highly noisy for magnetometer reading.

*2.3 Unscented kalman filter*

The dynamic system has been considered [12].The unscented transformation is an important part of the UKF, which uses a set of $(2n + 1)$ sigma points to approximate the Gaussian posterior density and the Gaussian predictive density.

Assemble the complete UKF as the followings:

- Initialization

Select any initial mean and its positive definite error covariance matrix $x_{0|-1}$ and $P_{0|-1}$respectively

- Time update

Determined initial states

$$e = \hat{x}_{k-1|k-1}(1:3)$$
$$e_0 = \hat{x}_{k-1|k-1}(4)$$
$$\hat{q}_{ref} = [e^T, e_0]^T,$$

And bias

$$b_{a(k-1)} = \hat{x}_{k-1|k-1}(5:7)$$
$$b_{\omega(k-1)} = \hat{x}_{k-1|k-1}(8:10)$$
$$b_{magn(k-1)} = \hat{x}_{k-1|k-1}(11:13).$$

The inverse of $q$ is $\hat{q}_{ref}^{-1} = [-e^T, e_0]^T$.
After, we can be computed

$$A = \sqrt{P_{k-1|k-1}}, \quad (A = chol(P_{k-1|k-1}, 'lower')$$
$$\delta\hat{x}_{k-1|k-1} = [0,0,0, b_{a(k-1)}, b_{\omega(k-1)}, b_{magn(k-1)}]^T$$
$$\delta\hat{X} = \partial\hat{x}_{k-1|k-1}[1 \ \dots \ 1] + [0_{6\times1} \ A \ -A]\frac{1}{n+\lambda}.$$

Next, we are going to propagate in a close loop for a time update
If $i = 1:nsigma$

$$\delta\hat{q}_{k-1|k-1} = \left[\frac{\delta\hat{X}(1:3, \ i)}{\sqrt{1 - \delta\hat{X}(1:3, \ i)^T\delta\hat{X}(1:3, \ i)}}\right]$$
$$\hat{q}_{k-1|k-1} = \delta\hat{q}_{k-1|k-1} \otimes \hat{q}_{ref}$$
$$b_{a(k-1|k-1)} = \delta\hat{X}(4:6, \ i)$$
$$b_{\omega(k-1|k-1)} = \delta\hat{X}(7:9, \ i)$$
$$b_{magn(k-1|k-1)} = \delta\hat{X}(10:12, \ i),$$
$$\hat{X}_{k-1|k-1}(:,i) = [\hat{q}^T{}_{k-1|k-1}, b^T{}_{a(k-1|k-1)} \cdots b^T{}_{\omega(k-1|k-1)}, b^T{}_{magn(k-1|k-1)}]^T.$$
$$\hat{X}_{k|k-1}(:,i) = f_d\left(u_{k-1}, \hat{X}_{k-1|k-1}(:,i), Ts\right),$$
$$e = \hat{X}_{k|k-1}(1:3,i) \quad ; e_0 = \hat{X}_{k|k-1}(4,i)$$
$$b_{a(k|k-1)} = \hat{X}_{k|k-1}(5:7,i)$$
$$b_{\omega(k|k-1)} = \hat{X}_{k|k-1}(8:10,i)$$
$$b_{magn(k|k-1)} = \hat{X}_{k|k-1}(11:13,i)$$
$$\hat{q}_{k|k-1} = [e^T, e_0]^T$$
$$\delta\hat{q}_{k|k-1} = \hat{q}_{k|k-1} \otimes \hat{q}_{ref}{}^{-1}$$
$$\delta e = \delta\hat{q}_{k|k-1}(1:3)$$
$$\delta\hat{X}_{k|k-1}(:,i) = [\delta e^T{}_{k|k-1}, b^T{}_{a(k|k-1)} \cdots b^T{}_{\omega(k|k-1)}, b^T{}_{magn(k|k-1)}]^T.$$

End

So that, we can compute mean and covariance in time update

$$\delta\hat{x}_{k|k-1} = \delta\hat{X}_{k|k-1}W_m$$
$$\partial\hat{q}_{k|k-1} = \left[\frac{\delta\hat{x}_{k|k-1}(1:3)}{\sqrt{1 - \delta\hat{x}_{k|k-1}(1:3)^T\delta\hat{x}_{k|k-1}(1:3)}}\right]$$
$$\hat{q}_{k|k-1} = \delta\hat{q}_{k|k-1} \otimes \hat{q}_{ref},$$
$$P_{k|k-1} = \delta\hat{X}_{k|k-1}W\delta\hat{X}_{k|k-1}{}^T + Q_cT_s,$$
$$\hat{x}_{k|k-1} = [\hat{q}^T{}_{k|k-1}, \delta\hat{x}^T{}_{k|k-1}(4:6) \dots \delta\hat{x}^T{}_{k|k-1}(7:9), \delta\hat{x}^T{}_{k|k-1}(10:3)]^T.$$

- Measurement update

We have redetermined some parameters of the state equation:

$$e = \hat{x}_{k|k-1}(1:3), \quad e_0 = \hat{x}_{k|k-1}(4)$$
$$b_{a(k|k-1)} = \hat{x}_{k|k-1}(5:7),$$
$$b_{\omega(k-1|k-1)} = \hat{x}_{k|k-1}(8:10),$$
$$b_{magn(k-1|k-1)} = \hat{x}_{k|k-1}(11:13),$$
$$\hat{q}_{ref} = [e^T, e_0]^T,$$
$$\delta\hat{x}_{k|k-1} = [0,0,0, b_{a(k-1)}, b_{\omega(k-1)}, b_{magn(k-1)}]^T.$$

Then, we compute the sigma point

$$A = \sqrt{P_{k|k-1}},$$
$$\delta\hat{X}_{k|k-1} = \delta\hat{x}_{k|k-1}[1 \ \dots \ 1] + [0_{6\times1} \ A \ -A]\frac{1}{n+\lambda}.$$

Next, we are going to propagate in a close loop for a time update
If $i = 1:nsigma$

$$\delta\hat{q}_{k-1|k-1} = \left[\frac{\delta\hat{X}_{k|k-1}(1:3, \ i)}{\sqrt{1 - \delta\hat{X}_{k|k-1}(1:3, \ i)^T\delta\hat{X}_{k|k-1}(1:3, \ i)}}\right],$$
$$\hat{X}_{k-1|k-1}(:,i) = \begin{bmatrix} \delta\hat{q}_{k|k-1} \otimes \hat{q}_{ref} \\ \delta\hat{X}_{k|k-1}(4:6,i) \\ \delta\hat{X}_{k|k-1}(7:9,i) \\ \delta\hat{X}_{k|k-1}(10:12,i) \end{bmatrix},$$
$$\hat{Y}_{k|k-1} = h_d\left(\hat{X}_{k-1|k-1}(:,i)\right).$$

End

$$\hat{y}_{k|k-1} = \hat{Y}_{k|k-1}Wm$$
$$P_{xy} = \delta\hat{X}_{k|k-1}W\hat{Y}^T{}_{k|k-1}$$
$$P_{yy} = \hat{Y}_{k|k-1}W\hat{Y}^T{}_{k|k-1} + R$$
$$K_k = P_{xy}P^T{}_{yy}$$
$$\delta\hat{X}_{k|k} = \delta\hat{X}_{k|k-1} + K_k\left(y_k - \hat{y}_{k|k-1}\right)$$
$$\delta\hat{q}_{k|k} = \left[\frac{\delta\hat{X}_{k|k}(1:3)}{\sqrt{1 - \delta\hat{X}^T{}_{k|k}(1:3)\delta\hat{X}_{k|k}(1:3)}}\right]$$
$$\hat{q}_{k|k} = \delta\hat{q}_{k|k} \otimes \hat{q}_{ref}.$$

After that, we can find state estimation

$$\hat{x}_{k|k} = [\hat{q}^T{}_{k|k}, \delta\hat{x}^T{}_{k|k}(4:6) \dots \delta\hat{x}^T{}_{k|k}(7:9), \delta\hat{x}^T{}_{k|k}(10:3)]^T,$$
$$P_{k|k} = P_{k|k-1} - K_kP_{yy}K^T{}_k.$$

Where $nsigma = 2n + 1$ is called the set of number sigma points. $n$ is number of states. $W_m$ is mean contraction weight and

$W_c$ is covariance contraction weight. $W$ is weight of UKF that can be computed from $W_c$ and $W_m$ [12]. Note that the computation of the square root of a matrix $\sqrt{P}$, can be done using Cholesky factorization "chol(P)". And $\otimes$ can be produced by:

$$a \otimes b = \begin{bmatrix} a_4 & a_3 & -a_2 & a_1 \\ -a_3 & a_4 & a_1 & a_2 \\ a_2 & a_1 & a_4 & -a_3 \\ a_1 & -a_2 & a_3 & a_4 \end{bmatrix} \begin{bmatrix} b_1 \\ b_2 \\ b_3 \\ b_4 \end{bmatrix}.$$

## 3. RESULTS AND DISCUSSION

The experiment is carried out by using MATLAB & Simulink. The hardware is Pixhawk 4 controller. The purpose of the simulation is to study the effects of sensor noise. Therefore, the model of the sensors focuses on these aspects:

- The Gyro meter's signal is corrupted with noise.
- Accelerometers are corrupted with noise and high frequencies.
- Magnetometers are also corrupted with noise and high frequencies

The parameter of the experiment given to the system is, sampling $Ts = 0.01$s, sensors noise is a gaussian zero-mean with the standard deviation of $Qc$ and $R$ as shown in Table 1 and 2.

**Table 1** Parameter tuning of $Qc$

| parameter | $Qc$ |
|---|---|
| Quaternion | $[10^{-9} \quad 10^{-9} \quad 10^{-9}]^T$ |
| RW | $[10^{-8} \quad 10^{-8} \quad 10^{-8}]^T$ |
| Bias Gyro meter | $[10^{-9} \quad 10^{-9} \quad 10^{-9}]^T$ |
| Bias Magnetometer | $[10^{-11} \quad 10^{-11} \quad 10^{-11}]^T$ |

**Table 2** Parameter tuning of $R$

| parameter | $R$ |
|---|---|
| Accelerometer | $[10^{-1} \quad 10^{-1} \quad 10^{-1}]^T$ |
| Magnetometer | $[10^{-1} \quad 10^{-1} \quad 10^{-1}]^T$ |

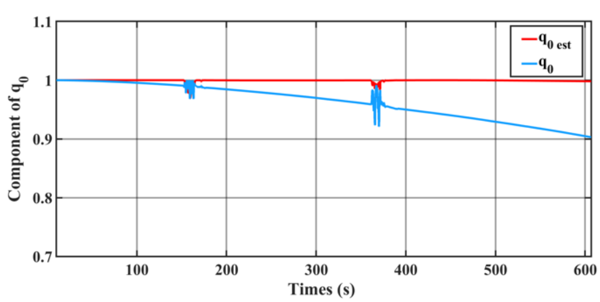


**Fig. 2.** Component of $q_0$

This is a result of $q_0$ component as expressed in Fig. 2. There are two lines in plotting that one is a red line label as $q_0$ obtained from estimation using UKF on the red line and the component from modeling computation on the blue line, respectively. We observed that at starting time, $q_0$ from estimation and $q_0$ from modeling, computation is stated to follow an initial condition in 1. After we have tested for a long time 600second, we have seen that $q_0$ from modeling is drifting down at any time, while $q_0$ from estimation by using UKF is stable at the same time. This phenomenon can be explained by the fact that integration builds up noise over time and converts it to drift, which produces unfavorable outcomes [13].

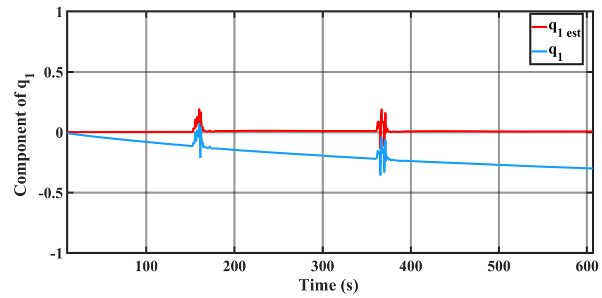


**Fig. 3.** Component of $q_1$

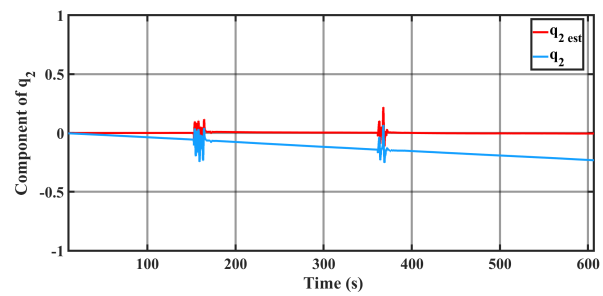


**Fig. 4.** Component of $q_2$

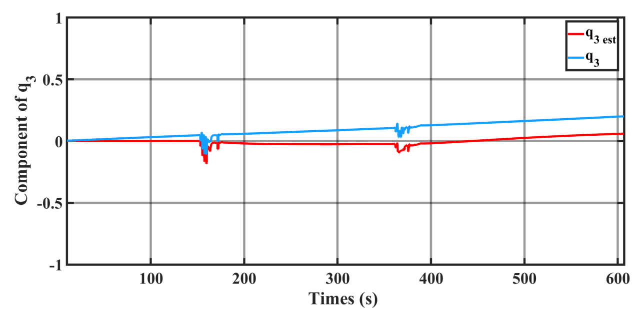


**Fig. 5.** Component of $q_3$

Three figures expressed in Fig. 3, Fig. 4, and Fig. 5 are result of attitude such as: $q_1, q_2, q_3$. If we refer to Euler angles, $q_1$ refers to roll angle, $q_2$ refers to pitch angle, and $q_3$ refers to yaw angle. Each graph features two lines: a red line that represents data estimated using the UKF algorithm utilizing sensor fusion, and a blue line that represents data calculated using quaternion modeling. In the performance of both comparisons, we can note that at starting time, $q_1, q_2, q_3$ from estimation and $q_1, q_2, q_3$ from modeling quaternion computation are following the initial condition $[0, 0, 0]$. After that, when we have tested for a long time in $600\, second$, the performance of $q_1, q_2, q_3$ from estimation and computation show that $q_1, q_2, q_3$ from computation is starting to drift over, although we did not move the motion of the hardware while , $q_1, q_2, q_3$ from estimation is stable. The time for experiment is $600\, second$ because we want to observer the performance of state when they were working long time. The explanation for this phenomenon is that the integration accumulates the noise over time and turns the noise into drift, which yields unacceptable results (Abyarjoo, 2015).

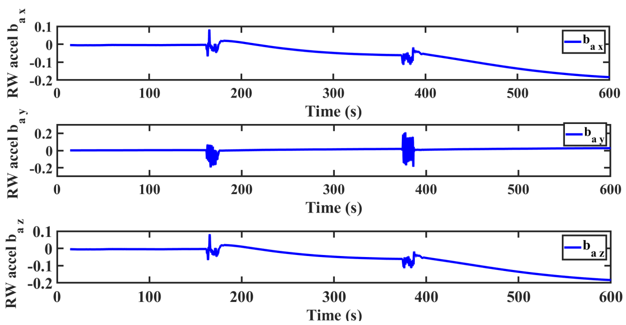


**Fig. 6.** Random walk accelerometer

Fig. 6. illustrates the random walk of the accelerometer sensor. The performance of a good random walk estimation is between $-0.2$ to $0.2$. The graph demonstrates that the line of $b_{az}, b_{ay}, b_{az}$ has been actively working to correct the estimation between time $160s$ - $180s$ and time $380s$ - $390s$ in order to correct the bias in the sensors because at that time, hardware created motion, so that random walk has been working hard to correct the estimation. These biases are not compensated for through the algorithm because of their negligible effect compared to the accelerometer biases.

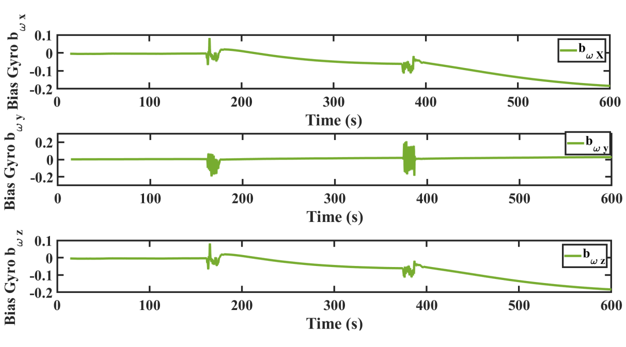


**Fig. 7.** Bias of Gyro meter

The Pixhawk 4's performance gyro rate bias is depicted in Fig. 7. The Pixhawk 4's performance gyro rate bias is depicted in $Q$ and $R$. The graph demonstrates that the line $b_{\omega z}, b_{\omega y}, b_{\omega z}$ working diligently to correct the sensor's bias between times $160s$ - $180s$ and time $380s$ - $390s$ because during those intervals, the hardware generated motion, which made it difficult for the estimation of bias. These biases are not compensated for through the algorithm because of their negligible effect compared to the gyro rate biases.

Fig. 8 represented about performance magnetometer bias of Pixhawk 4. For magnetometer, it creates a lot of bias that causes system error. However, after tuning parameters $Q$ and $R$ the system stabilizes. The graph shows that the line of $b_{mz}, b_{my}, b_{mz}$ attempting to correct the sensor's bias between time $160s$ - $180s$ and time $380s$ - $390s$ because during those times, the hardware was creating motion, which made estimation of bias difficult. These biases are not compensated for through the algorithm because of their negligible effect compared to the magnetometer biases.

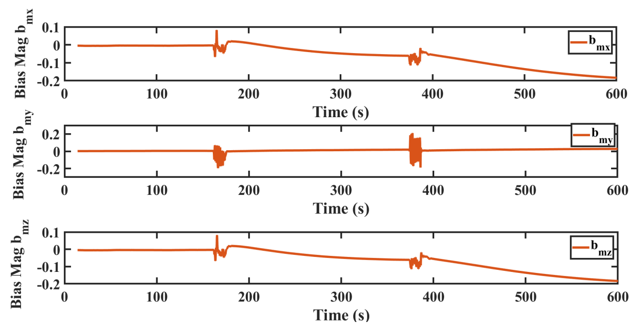


**Fig. 8.** Bias of Magnetometerma

## 4. CONCLUSIONS

In this paper, the attitude of quadrotors estimation based on the UKF algorithm is proposed. The mathematical formulation of the problem has been presented in terms of the quaternion approach. State equation is used data by getting gyro meter (angular velocity). The measurement update algorithm uses the accelerometer sensor data, and the magnetometer sensor data pose the next time update. The experiment is conducted by testing with Pixhawk PX4 controller with MATLAB & Simulink. The result shows that the information attitude from estimation is not giving drift when the hardware is stable and the performance of biased that those result is useful for accuracy performance of quadrotor. Therefore, the result findings validated the proposed algorithm's UKF proper performance.


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