

Fault Tolerant Attitude Estimation Strategy for a Quadrotor UAV under Total Sensor Failure

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Abstract: In this paper, we propose a conventional extended Kalman filter (CEKF) based new fault-tolerant scheme for the control of quadrotor drones suffering from a total failure of gyroscope sensor. The fault-tolerant conventional extended Kalman filter (FTCEKF) combines two conventional extended Kalman filters under the name CEKF1 and CEKF2 as well as a fault detection algorithm. In the case of nominal operation of the quadrotor, it is possible to obtain a sufficiently good estimation of the desired attitude, position and speed using the first conventional extended Kalman filter (CEKF1). However, in the presence of a total failure of the gyroscope, this filter leads to the collapse of the whole system. To overcome this type of scenarios, a second filter is used as a backup filter (CEKF2), where its role is to ensure a satisfactory attitude estimation using only a low cost magnetometer. To detect a gyroscope sensor failure, a reconfiguration mechanism based on a probabilistic algorithm to make a decision to switch to the backup filter is proposed in this article. The results show that the proposed (FTCEKF) scheme is approved to be robust against a total gyroscope failure with higher filtering performance.

Keywords: Quadrotor UAVs, Total sensor failure, Fault tolerant, Conventional extended Kalman filter, Reconfiguration mechanism, Grey Wolf Optimizer (GWO).

1. INTRODUCTION

Fault detection and diagnosis (FDD) and fault tolerant control (FTC) have become very important scientific research projects for air and space vehicles such as: satellites, civil aircraft, Unmanned Aerial Vehicles (UAVs), and so on (Isermann, 2005; Zhang and Jiang, 2008; Alwi et al., 2011; Goupil, 2011). When subjected to total/partial failures of sensors, actuators, or factory faults (Abbaspour et al., 2020), the whole system can be lead to a collapse. Advanced devices in this area must be designed to eliminate the effects of these fault types.

Drones or UAVs are among the devices that are increasingly used in the military and civil domains. The UAVs are showing a growing interest for applications such as surveillance and rescue missions in dangerous environments. For this purpose, many algorithms are applied in order to reduce the risk and improve the localization accuracy of those aerial vehicles. In general, several approaches in the literature related to fault tolerance control systems are widely recognized in many papers. In works (Maybeck and Stevens, 1990; Rauch, 1995; Zhang and Jiang, 2001), the authors present a reconfiguration of the design of the control system when there is a presence of faults on the sensors/actuators in order to ensure the dynamic performance and the stability of the system. Examples of application areas are: aviation and interceptor terminal guidance with unknown target manoeuvres. A fault-tolerant control scheme proposed by (Qi

et al., 2007) is designed to automatically compensate the UAV actuator failures by introducing actuator health coefficients (AHC) into the rotorcraft UAV dynamic equation (RUAV). This approach is based on a new adaptive unscented Kalman filter (AUKF) used to actively estimate actuator failures. Two nonlinear adaptive estimators are designed to isolate and estimate partial sensor bias faults in the gyroscope and accelerometer. In addition there is use of a sliding mode observer to estimate the angles of roll and pitch only with accelerometer (Avram et al., 2015). In (Caliskan and Hajiyev, 2015; Caliskan and Hajiyev, 2016), the authors propose a fault-tolerant control system (FTC) to overcome sensor/actuator failures for unmanned aerial vehicles (UAV). This technique is based on the kalman filter (KF) and two-stage Kalman filters (TSKF) to detect and isolate faulty sensors and actuators. A new fault detection (FD) scheme based on a neural network adaptive observer is proposed for UAV to detect sensor and actuator faults as well as an EKF filter to tune learning coefficients in the aim of improving the accuracy and response speed of the Neural Network (NN) observer (Abbaspour et al., 2017). A comparison between the three filters of Madgwick, Mahony and that of extended Kalman in the orientation estimation of a movement is applied to a magnetic and inertial measurement unit (MIMU) embedded on a quadcopter. The results presented show that the Mahony filter offers a better estimation than the other filters (Ludwig and Burnham, 2018).

The EKF is used to improve the cooperative positioning accuracy of multiple UAVs. In the case of a GPS fault, a fault-tolerant navigation algorithm is proposed based on the EKF which guarantees secure navigation (Qu et al., 2017). A fault detection and isolation algorithm for the attitude estimation of an unmanned aerial vehicle (UAV) is integrated in a duplex IMU architecture in order to compensate for possible failures on the sensors (magnetometers, accelerometers and gyros) (D'Amato et al., 2018). An FTC design is applied for a quadcopter suffering from partial faults on the actuators. This solution is based on a bank of controllers containing a group of Sliding Mode Controllers (SMC), each controller is tuned for a specific fault (Merheb and Noura, 2019). A nonlinear FDD (Fault Detection and Diagnosis) strategy is proposed for a Helicopter with two degrees of freedom, dealing with the detection, identification, and classification of sensor, actuator and component faults using stochastic state estimation approaches. These approaches include IMM (Interacting Multiple Model)-EKF and IMM (Unscented Kalman Filter)-UKF for multiple fault conditions. The results obtained by the IMM-UKF give better fault detection performance (Raghappriya and Kanthalakshmi, 2020). A new fault-tolerant dynamics of a high-altitude, long-endurance unmanned aerial vehicle is proposed in the presence of a partial/total fault in the accelerometer. This technique is based on the Interactive Multiple Models (IMM) filter (Youn et al., 2020a). In (Youn, 2020), the use of a new Magnetic Fault Tolerant Navigation Filter (MFTNF) aims to guarantee the heading and position of the UAV, where it combines a primary KF using the magnetic field and a main KF to estimate attitude and position states, as well as an attitude and heading reference system (AHRS) without a magnetometer as a secondary backup filter. An AFTC (Active fault tolerant control) is proposed in the presence of partial faults on the sensors such as the barometer and the gyroscope along the X-axis of the UAV. Three filters are tested (EKF, UKF, CKF) to detect and isolate faults (Patan and Caliskan, 2022).

For the aforementioned articles, which deal with IMU sensor faults, we notice that some of them are based on the gyroscope and accelerometer sensors to estimate the attitude of the UAV. Without doubting their effectiveness for the considered application, these works nevertheless have limitations as described in Table 1.

To overcome these limitations (see Table 1), we propose a new attitude estimation design based on a UAV fault-tolerant system to ensure better drone stability in the case of a gyroscope total failure. In addition to the simplicity of this approach, it nevertheless constitutes a reliable and low cost solution due to the fact that it only uses software in its implementation, this allows avoidance of component redundancy.

The main aim of this work is to develop a fault-tolerant control strategy for a quad-rotor in case of total failure on the gyroscope. The latter will be designated under the name FTEKF which will be composed of two filters CEKF1, CEKF2 and a decision algorithm.

First, an extended Kalman filter (CEKF1) estimation algorithm based on gyroscope and magnetometer

measurements is used to estimate the attitude. In the case that the gyroscope fails, a probabilistic fault detection algorithm switches to the CEKF2 optimized fault-tolerant filter. This filter proves its reliability when only magnetometer measurements are used for attitude estimation. Three sliding mode controllers are applied to the quad-rotor, the first to control the attitude, the second for the altitude and the third to control the translational position. The rest of the article is organized as follows: Section 2 presents the nonlinear model and the quadrotor control laws. The different steps for the design of the fault-tolerant extended Kalman filter are discussed in section 3. The numerical simulation of the two filters CEKF1 and CEKF2 performances are done in section 4. Finally, the conclusion and future work are discussed in Section 5.

2. UAV DYNAMICS AND CONTROL

In this section, a description of the dynamic model equation is presented. Next, the attitude, altitude and position controllers are exposed.

2.1 Quadrotor dynamics model

To design an accurate fault-tolerant control system, the dynamic model of the quad-rotor would have to be the same. The model has six degrees of freedom $(x, y, z, \phi, \theta, \psi) \in \mathbb{R}^6$, where x, y are the coordinates in the horizontal plane and z is the vertical position, ϕ is the roll angle around axis x , θ is the pitch angle around axis y and ψ is the yaw angle around axis z (see Figure 1).

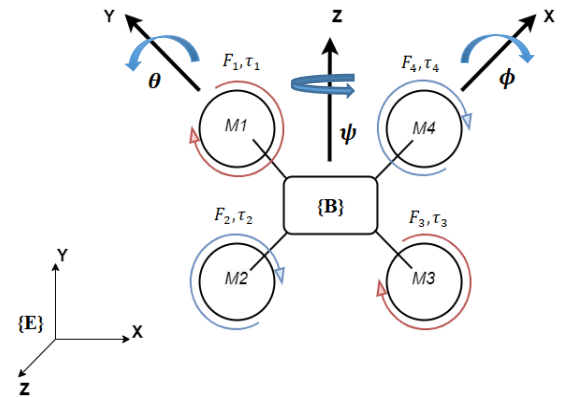


Fig. 1. Quadrotor Configuration.

In order to model the quadcopter UAV, the following assumptions were made (Bouadi et al., 2011)

Assumption 1 quadrotor is a rigid and symmetrical body. The propellers are also rigid.

Assumption 2 the lift and drag of each engine are proportional to the square of the propeller velocity.

Assumption 3 the center of mass and the origin of the frame coincide.

Table 1. Summary of state estimation methods related to sensors fault

References	Approaches	Limitations
[10], [16]	Model-based/ Adaptive UKF /EKF	Relies on partial faults of the gyroscope and accelerometer: this does not reflect the case of a total sensors fault.
[11], [12]	Model-based/ KF / Adaptive two-stage KF	
[13]	NN/EKF	High computational complexity: Need huge historical system performance data.
[20]	Model-based/KF	The states of the angular position of roll and pitch are not taken into account.
[21]	Model-based/ EKF / UKF/ CKF	Presence of a partial fault on the gyroscope sensor (the X-axis);position and velocity states are not taken into account.

The translational and rotational dynamics of a quadrotor can be summarized as follows (Hamel et al., 2002;Bouabdallah, 2007)

$$\begin{cases} \ddot{\phi} = a_1\dot{\psi}\dot{\theta} + a_2\dot{\phi}^2 + a_3\bar{\Omega}\dot{\theta} + b_1U_2 \\ \ddot{\theta} = a_4\dot{\psi}\dot{\phi} + a_5\dot{\theta}^2 + a_6\bar{\Omega}\dot{\phi} + b_2U_3 \\ \ddot{\psi} = a_7\dot{\phi}\dot{\theta} + a_8\dot{\psi}^2 + b_3U_4 \end{cases} \quad (1)$$

$$\begin{cases} \ddot{x} = a_9\dot{x} + (U_xU_1)/m \\ \ddot{y} = a_{10}\dot{y} + (U_yU_1)/m \\ \ddot{z} = a_{11}\dot{z} + (\cos\phi\cos\theta)U_1/m - g \end{cases} \quad (2)$$

With

$$\begin{cases} a_1 = \frac{I_x - I_y}{I_z}, a_2 = \frac{-K_{fax}}{I_x}, a_3 = \frac{-J_r}{I_x} \\ a_4 = \frac{I_z - I_x}{I_y}, a_5 = \frac{-K_{fay}}{I_y}, a_6 = \frac{J_r}{I_y} \\ a_7 = \frac{I_x - I_y}{I_z}, a_8 = \frac{-K_{faz}}{I_z}, a_9 = \frac{-K_{fdx}}{m} \\ a_{10} = \frac{-K_{fdy}}{m}, a_{11} = \frac{-K_{fdz}}{m} \\ b_1 = \frac{d}{I_x}, b_2 = \frac{d}{I_y}, b_3 = \frac{1}{I_z} \end{cases} \quad (3)$$

And

$$\begin{cases} \bar{\Omega} = \omega_1 - \omega_2 + \omega_3 - \omega_4 \\ U_x = \cos\phi\sin\theta\cos\psi + \sin\phi\sin\psi \\ U_y = \cos\phi\sin\theta\sin\psi - \sin\phi\cos\psi \end{cases} \quad (4)$$

Where $I = \text{diag}\{I_x, I_y, I_z\}$ is inertia matrix, K_{fax}, K_{fay} and K_{faz} are the aerodynamic coefficients of friction, K_{fdx}, K_{fdy} and K_{fdz} are the positive translational drag coefficients, J_r is rotor inertia, d is the distance between the center of gravity of the quadcopter and propellers rotation axis, $\omega_1, \omega_2, \omega_3$ and ω_4 the angular velocities of the quadcopter rotors, C_D is the drag coefficient and U_1, U_2, U_3 and U_4 are control inputs of the system.

Remark 1 assuming that ϕ and θ are small, $[p, q, r]^T$ can be likened to $[\dot{\phi}, \dot{\theta}, \dot{\psi}]^T$

2.2 Control law design

It is necessary to determine the control law of the quadrotor in order to exploit it in our filtering system. Three sliding mode controllers (SMC) are implemented on the quadrotor. an attitude controller generates the command inputs $[U_2, U_3, U_4]$ such that the Euler angles $[\phi, \theta, \psi]$ follow the desired attitude trajectory $[\phi_d, \theta_d, \psi_d]$. we also use an altitude controller for the vertical movement and a position controller following the coordinates (x, y) . The block diagram of the proposed controller is shown in Fig. 2.

The development of these controllers proposed by (Bouadi and Tadjine, 2007), can be summarized as follows

The quadcopter is defined with 12 states such that $[\phi, \dot{\phi}, \theta, \dot{\theta}, \psi, \dot{\psi}, x, \dot{x}, y, \dot{y}, z, \dot{z}]^T$

We have

$$\begin{cases} e_i = x_{id} - x_i \\ \dot{S}_i = \dot{e}_i + \lambda_i e_i \\ \ddot{S}_i = \ddot{e}_i + \lambda_i \dot{e}_i \end{cases} \quad i \in [1, 3, 5, 7, 9, 11] \quad (5)$$

$$\dot{S}_i = -k_i \text{sign}(S_i) \quad (6)$$

Where x_{id} is the desired state vector and e_i the error state vector, S_i is the sliding surface and $\dot{S}_i$ are their derivatives, $\text{sign}(-)$ is the saturation function to minimize the chatter of the discontinuous part of the controller, $(k_i, \lambda_i) \in \mathbb{R}^{+2}$ being the gains of the controllers.

Remark 2 The controllers gains (k_i, λ_i) are determined by a metaheuristic optimization method.

• Attitude Controller

We propose to calculate the control laws $U_2 \sim U_4$ in order to ensure stabilization at the roll, pitch and yaw angles.

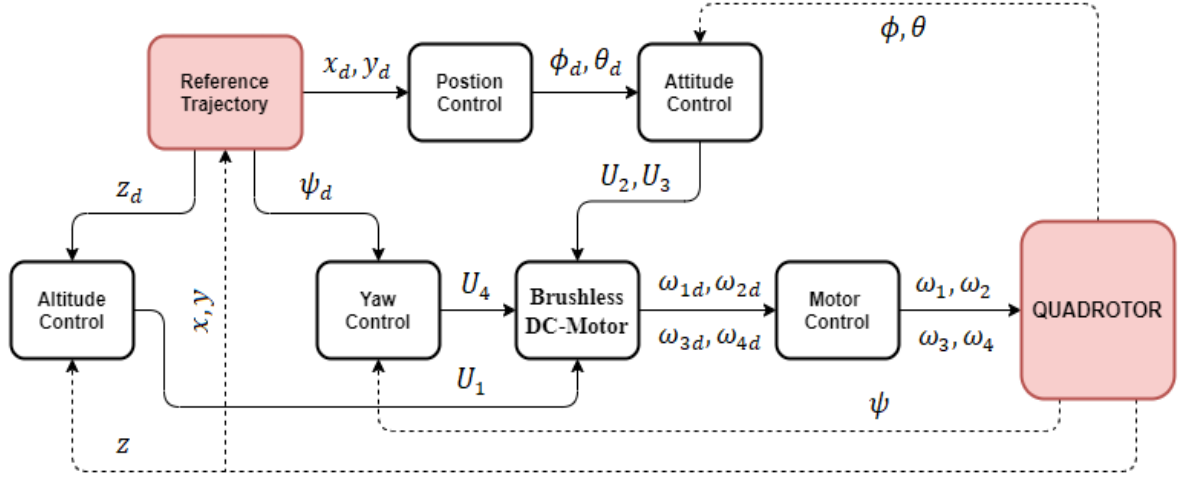


Fig. 2. Synoptic scheme of the proposed controller

For $i = 1$, we obtain from (7) the derivative of the sliding surface, which ensures convergence of the roll angle towards its reference value.

$$\begin{cases} \dot{S}_\phi = (\ddot{\phi}_d - \ddot{\phi}) + k_\phi(\dot{\phi}_d - \dot{\phi}) \\ \quad = -k_\phi \text{sign}(S_\phi) \end{cases} \quad (7)$$

We replace $\ddot{\phi}$ by its value described by (7), we obtain

$$-k_\phi \text{sign}(S_\phi) = (\ddot{\phi}_d - (a_1 \dot{\psi} \dot{\theta} + a_2 \dot{\phi}^2 + a_3 \bar{\Omega} \dot{\theta} + b_1 U_2)) + k_\phi(\dot{\phi}_d - \dot{\phi}) \quad (8)$$

We derive U_2 from (14) and the same steps are followed to find U_3 and U_4

$$\begin{cases} U_2 = \frac{1}{b_1} (k_\phi \text{sign}(S_\phi) - a_1 \dot{\theta} \dot{\psi} - a_2 \dot{\phi}^2 - a_3 \bar{\Omega} \dot{\theta} \\ \quad + \ddot{\phi}_d + \lambda_\phi(\dot{\phi}_d - \dot{\phi})) \\ U_3 = \frac{1}{b_2} (k_\theta \text{sign}(S_\theta) - a_4 \dot{\phi} \dot{\psi} - a_5 \dot{\theta}^2 + a_6 \bar{\Omega} \dot{\phi}) \\ \quad + \ddot{\theta}_d + \lambda_\theta(\dot{\theta}_d - \dot{\theta}) \\ U_4 = \frac{1}{b_4} (k_\psi \text{sign}(S_\psi) - a_7 \dot{\phi} \dot{\theta} - a_8 \dot{\psi}^2) + \ddot{\psi}_d \\ \quad + \lambda_\psi(\dot{\psi}_d - \dot{\psi}) \end{cases} \quad (9)$$

• Altitude Controller

The altitude subsystem is controlled from the command U_1 , consider the altitude error e_z is as follows

$$e_z = z_d - z \quad (10)$$

$$\dot{S}_z = (\ddot{z}_d - \ddot{z}) + k_z(\dot{z}_d - \dot{z}) \quad (11)$$

We replace $\ddot{z}$ by its value described by (8) and we deduce U_1

$$\begin{aligned} -k_z \text{sign}(S_z) = \\ \left(\ddot{z}_d - \left(a_{11} \dot{z} + \frac{(c\phi c\theta)U_1}{m} - g \right) \right) + \lambda_z(\dot{z}_d - \dot{z}) \end{aligned} \quad (12)$$

$$U_1 = \frac{m}{c\phi c\theta} (k_z \text{sign}(S_z) - a_{11} \dot{z} + \ddot{z}_d + \lambda_z(\dot{z}_d - \dot{z}) + g) \quad (13)$$

• Position Controller

This controller aims to obtain the desired Euler angles for position control. Consider that the errors e_x, e_y for x, y are

$$\begin{cases} e_x = x_d - x \\ e_y = y_d - y \end{cases} \quad (14)$$

$$\begin{cases} \dot{S}_x = (\ddot{x}_d - \ddot{x}) + \lambda_x(\dot{x}_d - \dot{x}) \\ \dot{S}_y = (\ddot{y}_d - \ddot{y}) + \lambda_y(\dot{y}_d - \dot{y}) \end{cases} \quad (15)$$

We replace $\ddot{x}$ and $\ddot{y}$ by their value described by (2) and we deduce U_x and U_y

$$\begin{cases} -k_x \text{sign}(S_x) = \\ (\ddot{x}_d - (a_9 \dot{x} + (U_x U_1)/m)) + \lambda_x(\dot{x}_d - \dot{x}) \\ -k_y \text{sign}(S_y) = \\ (\ddot{y}_d - (a_{10} \dot{y} + (U_y U_1)/m)) + \lambda_y(\dot{y}_d - \dot{y}) \end{cases} \quad (16)$$

$$\begin{cases} U_x = \\ \frac{m}{U_1} (k_x \text{sign}(S_x) - a_9 \dot{x} + \ddot{x}_d + \lambda_x(\dot{x}_d - \dot{x})) \\ U_y = \\ \frac{m}{U_1} (k_y \text{sign}(S_y) - a_{10} \dot{y} + \ddot{y}_d + \lambda_y(\dot{y}_d - \dot{y})) \\ , U_1 \neq 0 \end{cases} \quad (17)$$

Remark 3 The stability of these controllers in detail is discussed in [24].

3. ATTITUDE ESTIMATION AND DESIGN

The states of the quad-rotor model can be estimated via the CEKF filter, which combines the information of the model with the information of the sensors measurements in order to predict the best estimates of states, this filter is used throughout this work.

3.1 Sensor models

Three sensors are considered in this work, two attitude sensors to estimate the roll, pitch and yaw angles so that we exploit the kinematic relationships between the variables measured by these sensors, the gyroscope provides the angular velocity measurements and the three-axis magnetometer provides magnetic field strength measurements. A third sensor is used to estimate altitude. This consists of a GPS system that provides quadrotor position and speed measurements.

3.1 A Magnetometer model

The measurement of the magnetometer model can be given as follows (Ouyang and Abed-Meraim, 2022)

$$\tilde{M} = R_b [m_x \ m_y \ m_z]^T + \gamma_M \quad (18)$$

Such as

$$R_b = \begin{bmatrix} c\theta c\psi & s\phi s\theta c\psi - c\phi s\psi & c\phi s\theta c\psi + s\phi s\psi \\ c\theta s\psi & s\phi s\theta s\psi + c\phi s\psi & c\phi s\theta s\psi - s\phi c\psi \\ -s\theta & s\phi c\theta & c\phi c\theta \end{bmatrix} \quad (19)$$

Where $\tilde{M} = [\tilde{M}_x, \tilde{M}_y, \tilde{M}_z]^T$ are the actual measured values of the magnetometer, R_b is the transition matrix from the ground fixed frame {E} to the frame linked to the body of the quad-rotor {B}, $[m_x, m_y, m_z]^T$ are the magnetic fields measured in the navigation frame, $\gamma_M = [m_{bx}, m_{by}, m_{bz}]^T$ are the Gaussian white noise processes of zero average.

3.1 B Gyroscope model

The model of the gyroscope sensor is considered as following (Adnane et al., 2018b)

$$\tilde{G} = [p \ q \ r]^T + \gamma_G \quad (20)$$

Where $\tilde{G} = [\tilde{G}_x, \tilde{G}_y, \tilde{G}_z]^T$ are the actual values measured by the gyroscope, $[p, q, r]^T$ the true angular velocities of the UAV, γ_G is the zero-mean Gaussian noise of the gyroscope sensor.

3.1 C GPS model

The model relates to the position and speed information of the GPS receiver is as follows (Youn et al., 2020b)

$$\tilde{P} = [x \ y \ z]^T + \gamma_P \quad (21)$$

Where $\tilde{P} = [\tilde{P}_x, \tilde{P}_y, \tilde{P}_z]^T$, $[x, y, z]^T$ and γ_P are the actual positions measured by the GPS receiver, the true positions, and the zero-mean Gaussian position noise, respectively.

$$\tilde{V} = [\dot{x}, \dot{y}, \dot{z}]^T + \gamma_V \quad (22)$$

Where $\tilde{V} = [\tilde{V}_x, \tilde{V}_y, \tilde{V}_z]^T$, $[\dot{x}, \dot{y}, \dot{z}]^T$ and γ_V are the actual velocities measured by the GPS receiver, the true velocities, and the zero-mean Gaussian speed noise, respectively.

3.2 Fault tolerant conventional extended Kalman

The objective of this part concerns the development of a robust scheme with fault tolerances. In the presence of a total failure on the gyroscope, the filtering system becomes inaccurate and diverges easily. In this paper, an FTCEKF scheme based on two estimators (CEKF1, CEKF2) is applied on a quad-rotor to provide attitude knowledge with the desired accuracy. A reliable sensor fault detection algorithm is designed in order to make the decision to switch to the CEKF2 in the event that the gyroscope fails. Otherwise, we keep working with CEKF1 (See Figure3).

These proposed filters are implemented in two stages: propagation cycle and correction cycle. For the propagation stage it is the same for the two filters CEKF1 and CEKF2, on the other hand for the correction there will be a change in the cycle of this correction.

In order to simplify the formulas and equations below, it is assumed that $\eta = [\phi, \theta, \psi]^T$, $\omega = [p, q, r]^T$, $p = [x, y, z]^T$ and $v = [v_x, v_y, v_z]^T$. The augmented state vector to be estimated has 12 dimensions such that

$$X_k = [\eta, \omega, p, v]^T = [\phi, \theta, \psi, p, q, r, x, y, z, v_x, v_y, v_z]^T \quad (23)$$

Step 1 Propagation cycle

Based on the previous state of $\hat{X}_{k-1}$ and the error covariance matrix $\bar{P}_k$, we determine the predicted state $\bar{X}_k$ at instant k

$$\begin{cases} \bar{X}_k = f(\hat{X}_k, U_k) \\ \bar{P}_k = \Phi_k \bar{P}_k \Phi_k^T + Q_k \end{cases} \quad (24)$$

Such as

$$\bar{X}_k = [\bar{\eta} \ \bar{\omega} \ \bar{p} \ \bar{v}]^T \quad (25)$$

$$\Phi_k = I_{12 \times 12} \begin{bmatrix} \left. \frac{\partial \eta}{\partial \eta} \right|_{t=t_k} & \left. \frac{\partial \eta}{\partial \omega} \right|_{t=t_k} & \left. \frac{\partial \eta}{\partial p} \right|_{t=t_k} & \left. \frac{\partial \eta}{\partial v} \right|_{t=t_k} \\ \left. \frac{\partial \omega}{\partial \eta} \right|_{t=t_k} & \left. \frac{\partial \omega}{\partial \omega} \right|_{t=t_k} & \left. \frac{\partial \omega}{\partial p} \right|_{t=t_k} & \left. \frac{\partial \omega}{\partial v} \right|_{t=t_k} \\ \left. \frac{\partial p}{\partial \eta} \right|_{t=t_k} & \left. \frac{\partial p}{\partial \omega} \right|_{t=t_k} & \left. \frac{\partial p}{\partial p} \right|_{t=t_k} & \left. \frac{\partial p}{\partial v} \right|_{t=t_k} \\ \left. \frac{\partial v}{\partial \eta} \right|_{t=t_k} & \left. \frac{\partial v}{\partial \omega} \right|_{t=t_k} & \left. \frac{\partial v}{\partial p} \right|_{t=t_k} & \left. \frac{\partial v}{\partial v} \right|_{t=t_k} \end{bmatrix} T_s \quad (26)$$

Where $\bar{P}_k$ is the predicted error covariance matrix (12x12), Φ_k is the state transformation matrix of a dimension (12x12), Q_k is 12 by 12 process noise covariance matrix of dimension and T_s is the sampling period.

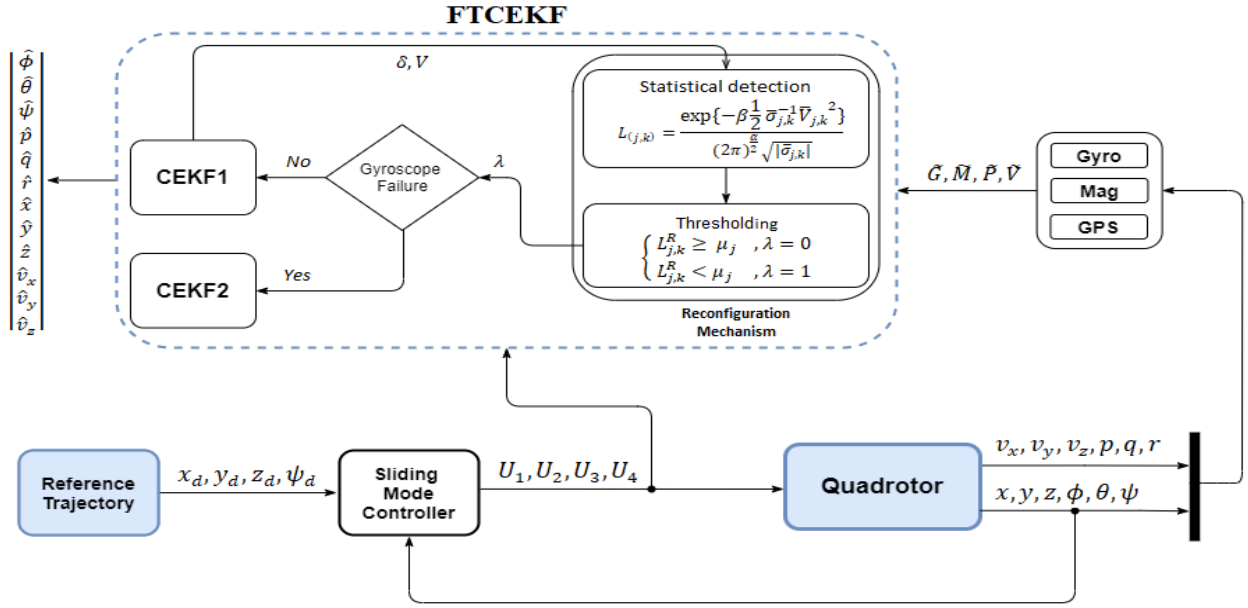


Fig. 3. Fault detection and estimation architecture

3.2 A CEKF1 correction cycle

It is considered that the gyroscope works in a nominal way therefore the observation matrix of dimension (12x12) is expressed by

$$H_k = \begin{bmatrix} \frac{\partial \tilde{M}}{\partial \eta} & \frac{\partial \tilde{M}}{\partial \omega} & \frac{\partial \tilde{M}}{\partial p} & \frac{\partial \tilde{M}}{\partial v} \\ \frac{\partial \tilde{G}}{\partial \eta} & \frac{\partial \tilde{G}}{\partial \omega} & \frac{\partial \tilde{G}}{\partial p} & \frac{\partial \tilde{G}}{\partial v} \\ \frac{\partial \tilde{P}}{\partial \eta} & \frac{\partial \tilde{P}}{\partial \omega} & \frac{\partial \tilde{P}}{\partial p} & \frac{\partial \tilde{P}}{\partial v} \\ \frac{\partial \tilde{V}}{\partial \eta} & \frac{\partial \tilde{V}}{\partial \omega} & \frac{\partial \tilde{V}}{\partial p} & \frac{\partial \tilde{V}}{\partial v} \end{bmatrix} \quad (27)$$

Kalman gain K_k and covariance matrix $\hat{P}_k$ are given for CEKF1 mode (Gelb, 1974; BROWN and HWANG, 1992).

$$K_k = \bar{P}_k H_k^T (H_k \bar{P}_k H_k^T + R_{CEKF1})^{-1} \quad (28)$$

$$\hat{P}_k = (I_{12 \times 12} - K_k H_k) \bar{P}_k \quad (29)$$

Such as

$$R_{CEKF1} = \text{diag}\{R_1, R_2, R_3, R_4\} \quad (30)$$

Where R_1, R_2, R_3, R_4 are the noise covariance matrices of the magnetometer, gyroscope, GPS position and GPS velocity measurements, respectively. Relying on the above equations (26), (28) and (29), the corrected state vector $\hat{X}_k = [\hat{\eta} \ \hat{\omega} \ \hat{p} \ \hat{v}]^T$ can be formed by the following equation

$$\hat{X}_k = \bar{X}_k + K_k \bar{\epsilon}_k \quad (31)$$

Such

$$\begin{cases} \bar{\epsilon}_k = Z_k - H_k \bar{X}_k \\ Z_k = [\tilde{M} \ \tilde{G} \ \tilde{P} \ \tilde{V}]^T \end{cases} \quad (32)$$

Where $\bar{\epsilon}_k$ is the corrected residual, Z_k is the output vector of sensor measurements: magnetometer, gyroscope, GPS position and GPS speed.

3.2 B CEKF2 correction cycle

There, we are in the situation where the gyroscope undergoes a breakdown, the observation matrix of dimension (12x9) becomes

$$H_k = \begin{bmatrix} \frac{\partial \tilde{M}}{\partial \eta} & \frac{\partial \tilde{M}}{\partial \omega} & \frac{\partial \tilde{M}}{\partial p} & \frac{\partial \tilde{M}}{\partial v} \\ \frac{\partial \tilde{P}}{\partial \eta} & \frac{\partial \tilde{P}}{\partial \omega} & \frac{\partial \tilde{P}}{\partial p} & \frac{\partial \tilde{P}}{\partial v} \\ \frac{\partial \tilde{V}}{\partial \eta} & \frac{\partial \tilde{V}}{\partial \omega} & \frac{\partial \tilde{V}}{\partial p} & \frac{\partial \tilde{V}}{\partial v} \end{bmatrix} \quad (33)$$

Kalman gain K_k and covariance matrix $\hat{P}_k$ for CEKF2 mode are given by

$$K_k = \bar{P}_k H_k^T (H_k \bar{P}_k H_k^T + R_{CEKF2})^{-1} \quad (34)$$

$$\hat{P}_k = (I_{12 \times 12} - K_k H_k) \bar{P}_k \quad (35)$$

Such

$$R_{CEKF2} = \text{diag}\{R_1, R_3, R_4\} \quad (36)$$

The corrected state vector $\hat{X}_k = [\hat{\eta} \ \hat{\omega} \ \hat{p} \ \hat{v}]^T$ can be formed by the equation

$$\hat{X}_k = \bar{X}_k + K_k \bar{\epsilon}_k \quad (37)$$

With

$$\bar{\epsilon}_k = [\tilde{M} \ \tilde{P} \ \tilde{V}]^T - H_k \bar{X}_k \quad (38)$$

3.2 C The probabilistic decision function

The most important process in the FTEKF scheme is the detection of a gyroscope sensor fault because faults cannot be

detected relying uniquely on the two estimators CEKF1 and CEKF2. To do this, a robust probabilistic algorithm is applied to the two filters in order to detect sensor faults as a first step and then make a decision to switch to the CEKF2 filter as a second step. Figure 3 shows a block diagram illustrating the proposed decision algorithm.

The statistical model proposed by (Adnane et al., 2018a) can be considered as our designed sensor fault detection device. The ability of this model is to identify the presence of a fault with a fast response time and without false alarms, this function can be defined as follows

$$L_{(j,k)}(\bar{V}_{j,k}, \bar{\sigma}_{j,k}) = \frac{1}{(2\pi)^{\frac{\alpha}{2}} \sqrt{|\bar{\sigma}_{j,k}|}} \exp \left\{ -\beta \frac{1}{2} \bar{\sigma}_{j,k}^{-1} \bar{V}_{j,k}^2 \right\} \quad (39)$$

Such

$$\bar{\sigma} = H_k \bar{P}_K H_k^T + R \quad (40)$$

Where $j = 1, 2, 3$ are the gyroscope j th axis of the, $\bar{V}_{j,k}$ the vector of gyroscope angular velocities, $\bar{\sigma}_{j,k}$ is residual covariance, α is the dimension of the measurement vector, β is the scalar penalty used to increase the detection performance.

The estimated change time of the fault occurrence is calculated by (41) and defined as

$$\bar{T}_{j,k}^R = \arg(L_{j,k}^R < \mu_j) \quad (41)$$

Where μ_j is the constant threshold characterizing the decision test as a function of the probability function. In the case where $L_{j,k}^R$ is lower than threshold μ_j , (42) calculates the time to appearance of the first fault and a fault signal is quickly declared. The decision rule then makes two assumptions

$$\begin{cases} L_{j,k}^R \geq \mu_j, \lambda = 0 \\ L_{j,k}^R < \mu_j, \lambda = 1 \end{cases} \quad (42)$$

Where λ is the sensor fault indicator (fault flag)

3.3 Design of GWO optimized

In this part, we use a GWO optimization algorithm to optimize the process noise covariance matrix $Q = [Q_1, Q_2, Q_3, Q_4]$. This algorithm, developed in 2014 by (Mirjalili et al., 2014), imitates the mechanisms of the leadership hierarchy. This method models the behaviors of a pack containing four types of gray wolves, three of which are used as leaders α , β , δ and subordinates ω (see Figure 4).

Each wolf represents a potential candidate solution and the prey is the optimum. The positions α , β and δ are updated taking into account their locations which obtain the best scores. A wolf (i) calculates its distance from the three optimal solutions by (43) – (45). Then we use (46) to update its position (Hu et al., 2020).

$$\begin{cases} \vec{A} = 2\vec{a} \cdot \vec{r}_1 - \vec{a} \\ \vec{B} = 2\vec{r}_2 \\ a = 2 - 2 * it / MAX_IT \end{cases} \quad (43)$$

Where $\vec{A}$ and $\vec{B}$ are two vectors of coefficients; it is the actual number of iterations and MAX_IT indicates the maximum number of iterations.

$$\begin{cases} \vec{D}_\alpha = |\vec{B} \cdot \vec{X}_\alpha - \vec{X}_i| \\ \vec{D}_\beta = |\vec{B} \cdot \vec{X}_\beta - \vec{X}_i| \\ \vec{D}_\delta = |\vec{B} \cdot \vec{X}_\delta - \vec{X}_i| \end{cases} \quad (44)$$

$$\begin{cases} \vec{X}_1 = \vec{X}_\alpha - \vec{A} \cdot \vec{D}_\alpha \\ \vec{X}_2 = \vec{X}_\beta - \vec{A} \cdot \vec{D}_\beta \\ \vec{X}_3 = \vec{X}_\delta - \vec{A} \cdot \vec{D}_\delta \end{cases} \quad (45)$$

$$\vec{X}_i(nt) = \frac{\vec{X}_1 + \vec{X}_2 + \vec{X}_3}{3} \quad (46)$$

Where $\vec{X}_i$, $\vec{X}_\alpha$, $\vec{X}_\beta$ and $\vec{X}_\delta$ represents the position vectors of i , α , β and δ ; $\vec{D}_\alpha$, $\vec{D}_\beta$ and $\vec{D}_\delta$ respectively mean the distance vectors between α , β , δ and i ; $\vec{r}_1$ and $\vec{r}_2$ are random vectors in the interval $[0, 1]$.

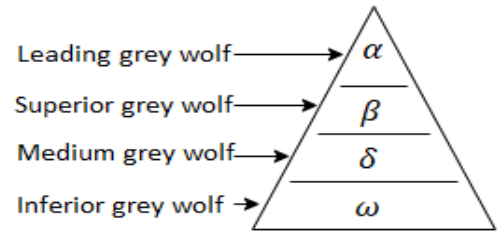


Fig4. The hierarchy of the grey wolf pack

4. RESULTS AND DISCUSSIONS

In this section, we perform simulations to validate the proposed fault tolerant mechanism. This simulation is based on the injection of a total failure to the gyroscope sensor in order to observe the behavior of the UAV and the efficiency of the mechanism that we propose to implement. The simulation was performed under MATLAB/Simulink environment. The total simulation time t_f is 200 sec and the sampling time is fixed at 0.01 sec. The simulations were carried out with the UAV parameters presented in Table 2.

To show the reliability and performance of the proposed fault tolerance mechanism FTCEKF we simulate two cases, the first is relying on the CEKF1 filter and the other uses the CEKF2 filter. Table 5 gives the performance of the two filters in terms of error verified by the root mean square (RMS) of the angles.

The Kalman filter is applied to merge the data from the magnetometer and the gyroscope during the phase before the

introduction of the failure, which means that after this incident the filter only works with the magnetometer.

For each one of the sensors, the noise covariance matrices R is selected for both filters in the same way. The covariance matrix Q of the process was selected for the CEKF1 filter empirically, on the other hand for the CEKF2 filter it was done empirically then and optimized by the GWO method (see Table 4).

The initial state of the filter estimator $(\hat{\phi}_0, \hat{\theta}_0, \hat{\psi}_0, \hat{p}_0, \hat{q}_0, \hat{r}_0, \hat{X}_0, \hat{Y}_0, \hat{Z}_0, \hat{V}_{x0}, \hat{V}_{y0}, \hat{V}_{z0}) = [0, 0, -\pi/3, 0, 0, 0, 0, 0, 0, 0, 0, 0]^T$, The initial error covariance matrix $\hat{P}_0 = 0.1 * \text{diag}[I_{12 \times 12}]$.

Table.2 Quadrotor general parameters

Specification	Parameter	Value
Quadrotor mass	m (Kg)	0.486
inertia on x axis	I_x (N.m/rad/s ²)	$3.8278e^{-3}$
inertia on y axis	I_y (N.m/rad/s ²)	$3.8278e^{-3}$
inertia on z axis	I_z (N.m/rad/s ²)	$7.6566e^{-3}$
distance	d (m)	0.25
aerodynamic friction torque along x	K_{fax} (N/rad/s)	$5.5670e^{-4}$
aerodynamic friction torque along y	K_{fay} (N/rad/s)	$5.5670e^{-4}$
aerodynamic friction torque along z	K_{faz} (N/rad/s)	$6.3540e^{-4}$
drag force along x	K_{fdx} (N/m/s)	$5.5670e^{-4}$
drag force along y	K_{fdy} (N/m/s)	$5.5670e^{-4}$
drag force along z	K_{fdz} (N/m/s)	$6.3540e^{-4}$
lift force coefficient	K_p (N.m/rad/s)	$2.9842e^{-5}$
drag force coefficient	C_D (N.m/rad/s)	$3.2320e^{-7}$
rotor inertia	J_r (N.m/rad/s ²)	$2.8385.e^{-5}$
mechanical torque constant	J_m	$3.1861e^{-3}$
rotor internal resistance	R (ohm)	0.4
solid friction	C_s	$5.3826e^{-3}$
electrical torque constant	K_e	0.0216
load constant torque	K_r	$3.4629e^{-7}$

A plenty of simulations have been carried out with different trajectories, the one proposed in this article consists of a helical trajectory, this trajectory may be presented in Table 3, with the initial position $(X_0, Y_0, Z_0) = [0, 0, 0]^T$ (m), and a final position $(X_f, Y_f, Z_f) = [-0.6, -1.9, 60]^T$ (m).

Table.3 input signals

State	Reference Trajectory	Time
x	$2 \cos(0.3\pi t)$	$[0 - t_f]$
y	$2 \sin(0.3\pi t)$	$[2 - t_f]$
z	t	$[0 - t_f]$
ψ	$0.1u(t)$	$[0 - t_f]$

The results of the simulations obtained by the CEKF2 filter are based on the optimization by the GWO method. The figures illustrating these optimized results are Figures 9 to 14. For each scenario we will try to make our simulation as realistic as possible by adding certain constraints such as

- Roll angle $\phi, -\pi/2 < \phi < \pi/2$
- Pitch angle $\theta, -\pi/2 < \theta < \pi/2$
- Yaw angle $\psi, -\pi < \psi < \pi$
- Introduction of noise in the response of the sensors
- Introduction of a fault at the level of the gyroscope.

4.1 CEKF1 application case

In this scenario, we are testing the fault tolerance of this filter. During the first, 30 sec all the sensors work correctly, then from time $t = 30$ sec we inject a total failure on the gyroscope sensor.

Figures 5, 6 and 7 show the capacity of this filter during the first 30 sec. The estimator follows the attitude angles with sufficient precision (stabilization after a period of less than 2 sec). What can be noticed from these graphs is a deterioration of the attitude angles after injecting a sensor fault.

Regarding the error, as shown in Figure 8, it remains in a range approximately between -1 and +1 deg, before the occurrence of the fault after which it begins to increase until the loss of stability (divergence).

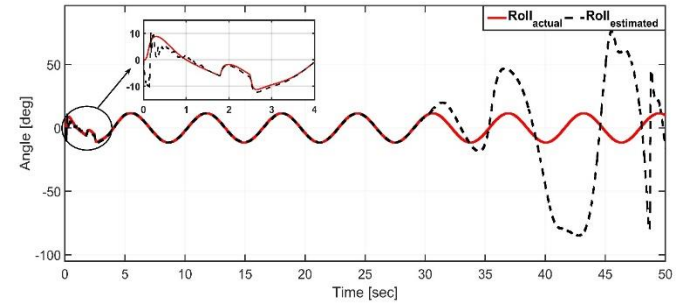


Fig. 5. Roll response of the system using CEKF1 in the case of gyroscope failure

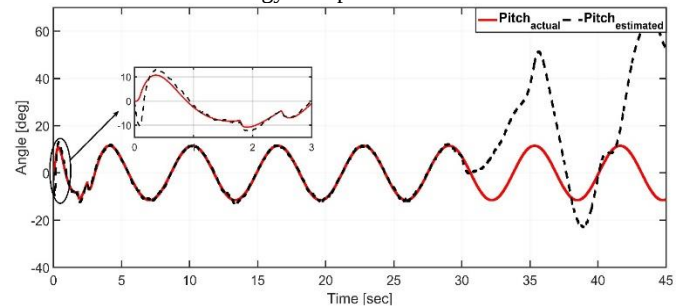


Fig. 6. Pitch response of the system using CEKF1 in the case of gyroscope failure

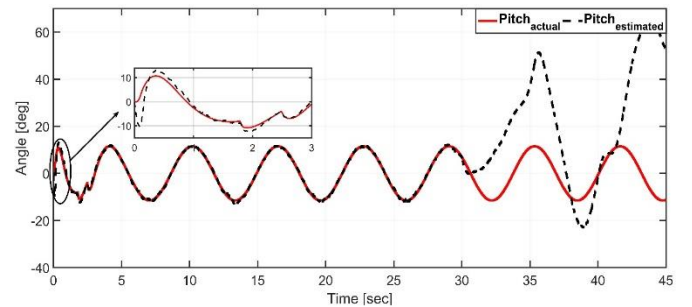


Fig. 7. Yaw response of the system using CEKF1 in the case of gyroscope failure

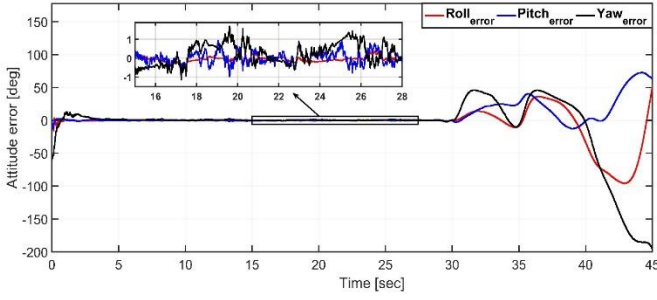


Fig. 8. Quadrotor attitude error estimation using CEKF1

According to the description of the simulations carried out above, we notice that the loss of a gyroscope will automatically lead to a total loss of attitude control of the UAV, the magnetometer alone cannot ensure correct information of the attitude. It is for this reason that we will rather move towards another filter structure that will have to be more tolerant to this type of fault. This will be achieved through the CEKF2 filter.

4.2 CEKF2 application case

The proposed fault tolerance mechanism is based on a probabilistic process obtained from (39). This proposed L^G statistical process provides extremely useful and correct information to detect faults without false alarms. The CEKF2 is triggered in the event that the probabilistic function detects a sensor failure.

Figures 9-a and 9-b show, on one hand, the change in the value of the statistical function L^G , for $\beta = 0.011$, at time $t = 30.42 \text{ sec}$ with a small delay of duration $\Delta t = 0.42 \text{ sec}$ to detect a total loss of the gyroscope. On the other hand, when L^G is lower than the constant threshold $\mu = 3.08125$, this indicates that we are still in a nominal case. A fault flag is used to differentiate between the nominal state and the state with a failure. That is to say, the λ flag is used by the mechanism to switch to CEKF2 when a sensor failure is detected.

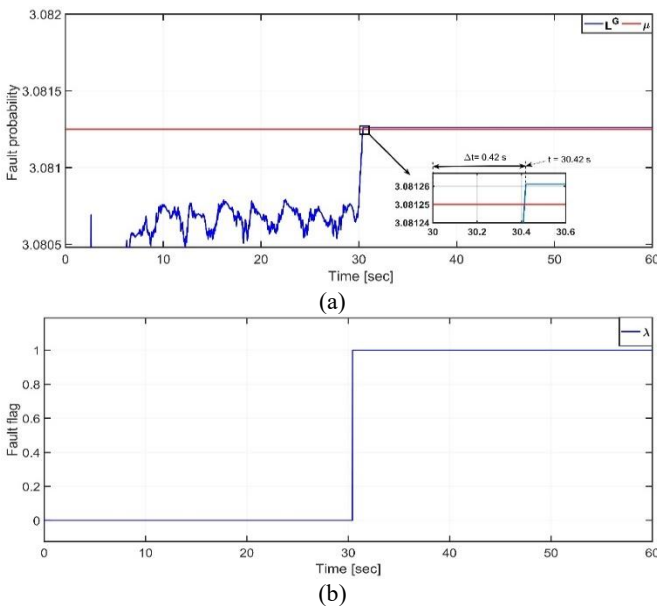


Fig. 9. Fault detection in the gyroscope for CEKF2: (a) fault probability, (b) fault flag.

As shown in Figures 10, 11 and 12, the proposed estimator is able to handle a total gyroscope sensor failure and follow the real attitude of the UAV. For roll and pitch the filter stabilizes from $t = 1.5 \text{ sec}$; for the yaw, the estimator starts at the angle -60 deg due to the initial state of the filter $\hat{\psi}_0$. The instant the probabilistic function detects that the gyroscope has failed, it causes a small deviation in the angle responses, $RMS_\phi = 0.31 \text{ deg}$ and $RMS_\theta = 0.7 \text{ deg}$ over an interval $t \in [30, 32]$ and for the yaw $RMS_\psi = 0.8 \text{ deg}$ over an interval $t \in [30, 45] \text{ sec}$.

Figure 13 shows the errors on the three attitude axes. In the nominal case the error is between $+1$ et -0.5 deg , on the other hand, after the failure of the sensor the error is between $+1.5$ and -0.5 deg . It is clear through this figure that the attitude estimate after the sensor failure has remained stable in comparison with the case where the CEKF1 filter is used.

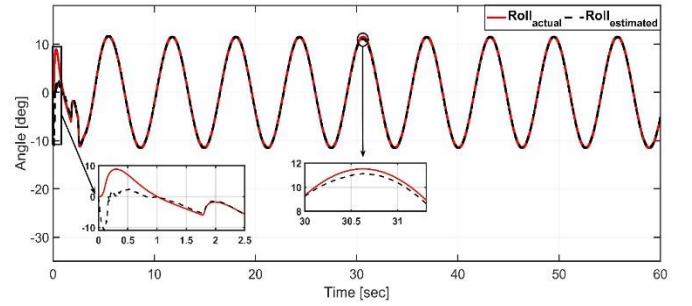


Fig. 10. Roll response of the system using CEKF2 in the case of gyroscope failure

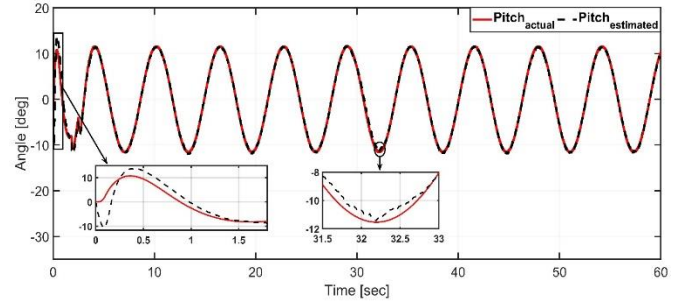


Fig. 11. Pitch response of the system using CEKF2 in the case of gyroscope failure

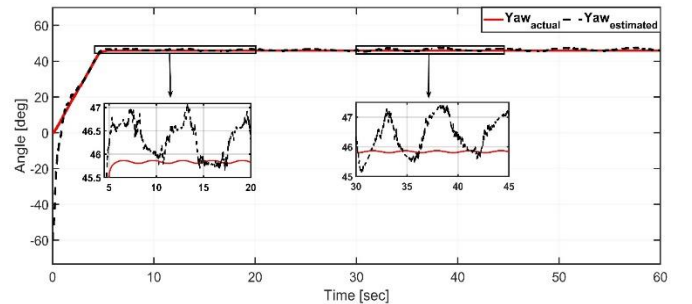


Fig. 12. Yaw response of the system using CEKF2 in the case of gyroscope failure

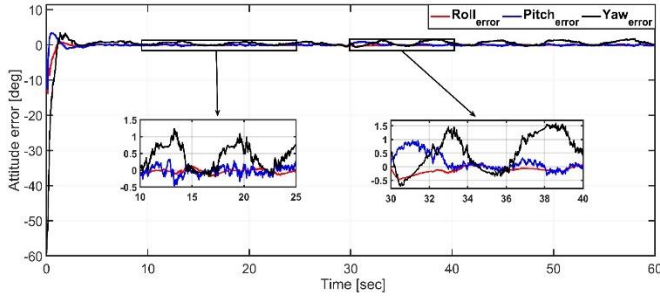


Fig. 13. Quadrotor attitude error estimation using CEKF2

Figures 14-a, 14-b and 14-c illustrate how the different angular velocities estimated by the CEKF2 filter progress and show that the stability has not been greatly affected.

Figure 15 shows that the proposed fault tolerance mechanism is done quickly without trajectory deviation, the figure displays the latter from the moment of detection of the failure by the L^G function, which starts at the position $(\hat{X}_L, \hat{Y}_L, \hat{Z}_L) = (-1.68, 1.08, 30.43)^T (m)$ and ends at the final position of the filter $(\hat{X}_f, \hat{Y}_f, \hat{Z}_f) = (-0.59, -1.91, 59.9)^T (m)$

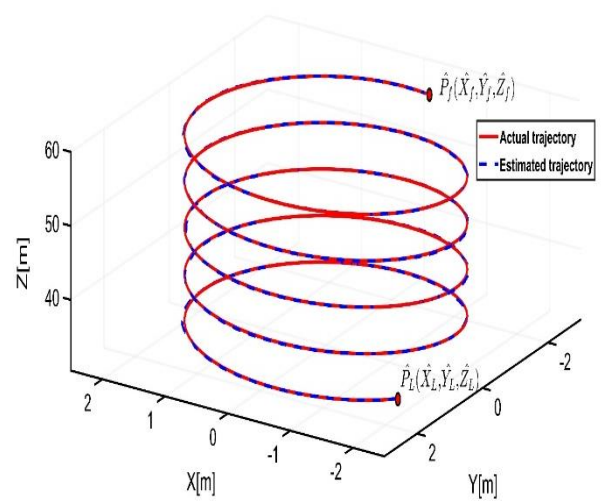


Fig. 15. Trajectory response of the system using CEKF2 in the case of gyroscope failure

As mentioned in Table 5 for the CEKF2 filter, an optimization was done by the GWO algorithm to determine the process noise covariance matrices Q_1, Q_2, Q_3 and Q_4 . Note that the choice of the fitness function (ff) is very important, to obtain a minimization and convergence of this function using the mean square error (MSE), this function is determined as follows

$$\begin{cases} ff = \frac{1}{MSE_i + 0.1} \\ MSE_i = \frac{\sum_{t=0}^f e_i^2}{size(e_i)} \\ e_i^2 = e_\phi^2 + e_\theta^2 + e_\psi^2 + e_p^2 + e_q^2 + e_r^2 \end{cases} \quad (47)$$

Where the attitude error values are represented by e_ϕ, e_θ and e_ψ and the angular velocities error values are represented by e_p, e_q and e_r .

After several simulation tests, the best values of the cost criterion (MSE) were obtained with a number of 10 agents. The GWO parameters are presented in Table 4 as well as Figure 16 that shows the convergence of the fitness function by the GWO algorithm.

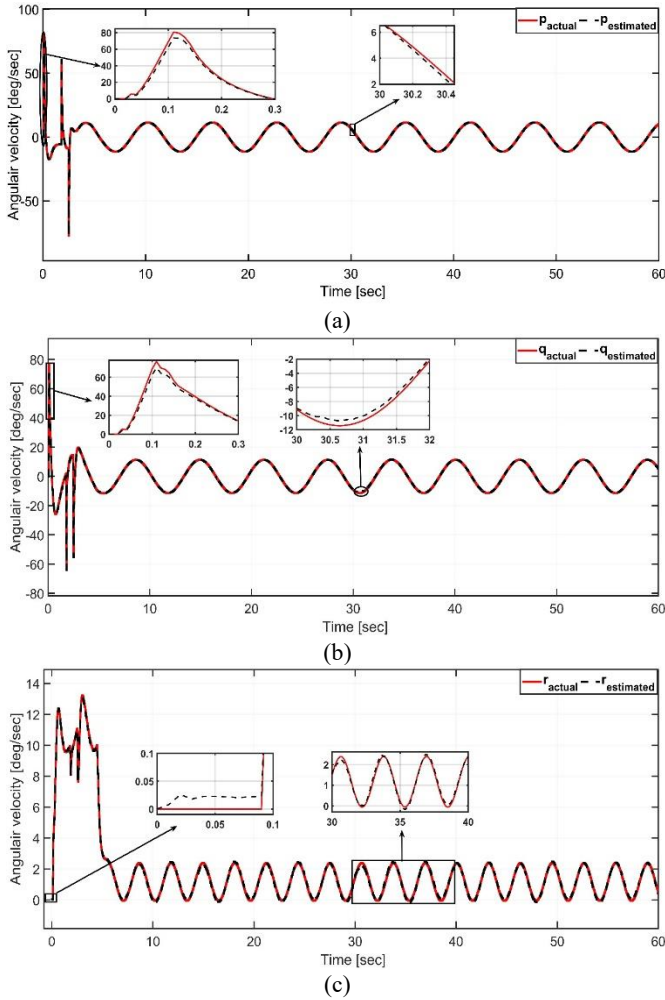


Fig. 14. Response of the system using CEKF2 in the case of gyroscope failure: (a) Angular velocity (p), (b) Angular velocity (q), (c) Angular velocity (r)

Table 4. The control parameters for GWO algorithm

Parameters	GWO
Number of search agents	10
Maximum iteration	15
Dimension	4
α	0.04336363
β	0.04336368
δ	0.04336370
r_1	0.5713
r_2	0.0550
X_1	1.0091e-12
X_2	9.8960e-13
X_3	9.8138e-12

Table 5. RMS values of the estimation errors of the filters CEKF1 and CEKF2

Filters	Gyroscope	Optimisation	RMS_ϕ (deg)	RMS_θ (deg)	RMS_ψ (deg)	Magnitude of Error (deg)	R	Q
CEKF1	No failure $t \in [0,30]$	Not optimised	0.161	0.387	0.740	0.8509	$R_1 = 0.3 \cdot I_{3 \times 3}$ $R_2 = 0.05 \cdot I_{3 \times 3}$ $R_3 = 0.1 \cdot I_{3 \times 3}$ $R_4 = 0.1 \cdot I_{3 \times 3}$	$Q_1 = 7.61 \cdot 10^{-11} I_{3 \times 3}$ $Q_2 = 6.72 \cdot 10^{-7} I_{3 \times 3}$ $Q_3 = 2.44 \cdot 10^{-8} I_{3 \times 3}$ $Q_4 = 2.70 \cdot 10^{-10} I_{3 \times 3}$
	With Failure $t \in]30,45]$	Not optimised	18.803	20.425	30.833	41.483		
CEKF2	With Failure $t \in]30,60]$	Not optimised	0.173	0.291	1.167	1.215	$R_1 = 0.3 \cdot I_{3 \times 3}$ $R_3 = 0.1 \cdot I_{3 \times 3}$ $R_4 = 0.1 \cdot I_{3 \times 3}$	$Q_1 = 4.00 \cdot 10^{-7} I_{3 \times 3}$ $Q_2 = 8.50 \cdot 10^{-7} I_{3 \times 3}$ $Q_3 = 7.50 \cdot 10^{-6} I_{3 \times 3}$ $Q_4 = 7.00 \cdot 10^{-5} I_{3 \times 3}$
		Optimised	0.119	0.241	0.839	0.881		$Q_1 = 9.39 \cdot 10^{-7} I_{3 \times 3}$ $Q_2 = 1.00 \cdot 10^{-7} I_{3 \times 3}$ $Q_3 = 2.78 \cdot 10^{-6} I_{3 \times 3}$ $Q_4 = 8.36 \cdot 10^{-5} I_{3 \times 3}$

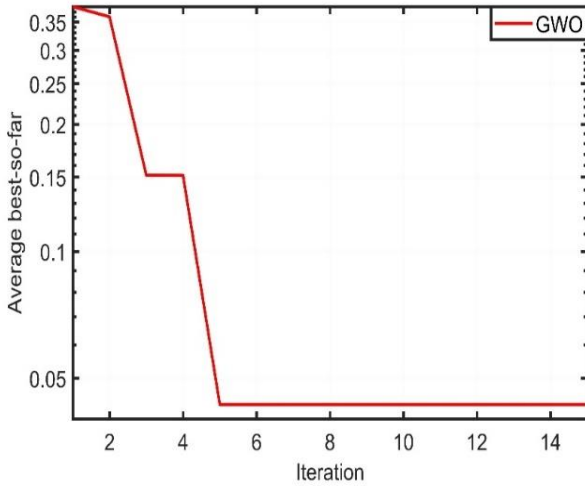


Fig. 16. The convergence curve of the GWO algorithm

5. CONCLUSION

In this paper, two extended Kalman filter based attitude estimation algorithms are developed with the introduction of total gyroscope failure to ensure high and reliable accuracy estimation of the UAV attitude. The results of the simulations show that the CEKF2 algorithm is highly reliable in accurately estimating the attitude and this is due to the quality of faults tolerance. On the other hand, in the nominal case the CEKF1 gives a stable attitude estimate, nevertheless it diverges when a failure of the gyroscope is introduced. Moreover, the fault tolerance mechanism based on the probabilistic function gives complete satisfaction when it is necessary to switch from CEKF1 to CEKF2. The CEKF2 algorithm can also be used as an alternative solution to secure the UAV mission. In future work, we plan to carry out experimental tests in order to validate the results obtained on a real quadrotor.

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