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FAULT DIAGNOSIS IN A NETWORKED CONTROL SYSTEM UNDER COMMUNICATION CONSTRAINTS: A QUADROTOR APPLICATION

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This paper considers the problem of attitude sensor fault diagnosis in a quadrotor helicopter. The proposed approach is composed of two stages. The first one is the modelling of the system attitude dynamics taking into account the induced communication constraints. Then a robust fault detection and evaluation scheme is proposed using a post-filter designed under a particular design objective. This approach is compared with previous results based on the standard Kalman filter and gives better results for sensor fault diagnosis.

Keywords: networked control systems, transmission delays, robust residual generation, adaptive residual evaluation.

1. Introduction

Unmanned aerial vehicles (UAVs) have received a great deal of attention during the last few years due to their high performance in several applications such as search and critical missions, surveillance tasks, geographic studies and various military and security applications. As an example of UAV systems, the quadrotor helicopter is a relatively simple, affordable and easy-to-fly system, and thus it has been widely used to develop, implement and test-fly methods in control, fault diagnosis, fault tolerant control as well as multi-agent based technologies in formation flight. Navigation and guidance algorithms may be embedded on the on-board flight microcomputer/micro-controller, or with the remote interference of ground wirelesses/wired controllers. In our setting the quadrotor is controlled over a real time communication network with time-varying delays and therefore is considered a networked control system (NCS). In general, the NCS is composed of a large number of interconnected devices (system nodes) that exchange data through a communication network.

Recent research on NCSs has received considerable attention in the automatic control community (Niculescu, 2001; Tipsuwan and Chow, 2003; Mirkin and Palmor, 2005; Hespanha *et al.*, 2007; Richard, 2003; Fang *et al.*, 2007). The major focus of the research activities are on system performance analysis regarding the technical properties of the network and on controller design schemes for NCSs (Xia *et al.*, 2011; Bemporad *et al.*, 2010).

However, the introduction of communication networks in the control loops makes the analysis and synthesis of NCSs a highly complex task (Morawski and Zajączkowski, 2010). There are several network-induced effects that arise when dealing with the NCS, such as time-delays (Niculescu, 2001; Nilsson *et al.*, 1998; Pan *et al.*, 2006; Schöllig *et al.*, 2007; Yi *et al.*, 2007; Zhang *et al.*, 2005), packet losses (Xiong and Lam, 2007; Sahebsara *et al.*, 2007; Yu *et al.*, 2004; Georges *et al.*, 2011) and quantization problems (Goodwin *et al.*, 2004; Montestruque and Antsaklis, 2007; Fang *et al.*, 2007). Because of the inherent complexity of such systems, the control issues of NCSs have attracted attention of many researchers, particularly taking into account network-induced effects. A typical application of these systems ranges over various fields, such as automotive engineering, mobile robotics, or advanced aircraft.

Fault diagnosis is one of the most important research fields in modern control theory (Frank and Ding, 1997; Gertler, 1998; Isermann, 2005; Stoustrup and Zhou, 2008; Basseville and Nikiforov, 1993). However, the study of fault detection (FD) of the NCS is a new research topic that has been receiving more attention in the last few years

(Simon *et al.*, 2013). For instance, the results of Sauter and Boukhobza (2006), Llanos *et al.* (2007) and Chabir *et al.* (2008; 2009; 2010) focus on networked-induced delays. The problem studied by Zhang *et al.* (2004) and Wang *et al.* (2009) is the analysis and design of FD systems in case of missing measurements. Fault detectability and isolability in NCSs have been discussed by Sauter *et al.* (2009), Chabir *et al.* (2009) or Sid *et al.* (2012). The fault tolerant structure is studied by Patton *et al.* (2007), Jain *et al.* (2012) and Jamouli *et al.* (2012). A method based on the reference governor can be found in the work of Weber *et al.* (2012).

Delays are known to drastically degrade the performance of control systems. For this reason, many works aim at reducing the effects of induced network delays on NCSs (Tipsuwan and Chow, 2003; Yu *et al.*, 2004; Li *et al.*, 2006). In the majority of the studies concerning NCSs, the delay is classified according to its nature either as deterministic or stochastic delay. It can also be classified as long or short delay, according to its duration. The delay is said to be short if its duration is less than one sampling period and long otherwise (Hu and Zhu, 2003; Lincoln and Bernhardsson, 2000). Generally, the dynamics of the delay corresponding to the characterization of the network are not taken into account. Thus, one interesting approach is to estimate the delay, in order to generate an optimal control, as well as robust algorithms of faults detection that take into account the network characteristics.

For dealing with the short delay effect, many works have been proposed in the literature. For instance, Sauter *et al.* (2009) formulate the delay effect as an unknown input with a variable distribution matrix by using Taylor approximation. The same approximated model is used by Ye and Ding (2004) for the generation of a time varying parity space based fault indicator. Stochastic delay can be modelled by a Markov chain (Yi *et al.*, 2007; Zhang *et al.*, 2005). Sauter *et al.* (2009) use a fault isolation filter for monitoring a system under Markovian short delays. The proposed filter parameters are designed using linear matrix inequalities (LMIs) (Boyd *et al.*, 1994). Zheng *et al.* (2003) propose a reduced order fault detection filter for improving the robustness to constant long delay and reduce the complexity of the design problem.

Wang *et al.* (2006) set forth a method for fault detection in NCSs under stochastic and probably long duration delay. The model given by Ray and Halevi (1988) as well as Hu and Zhu (2003) is adopted for the design. However, this model can be seen as an extension of the unidimensional Taylor approximation given by Ye and Ding (2004) for the multidimensional case. Wang *et al.* (2008) consider mixed delay composed of a constant part and random part. The delay effect is approximated by polytopic uncertainties and uses the "reference model" fault detection technique (Ding, 2008) for the design

of observer based fault detection. A majority of fault detection approaches of NCSs that exist in the literature are model based (Sauter *et al.*, 2013). However, artificial intelligence methods are considered less suitable for real time implementation (Rahmani *et al.*, 2008).

The objective in this study is the diagnosis of quadrotor attitude sensors fault under variable transmission delay. First, an attitude dynamic model taking into account variable transmission delay is presented. Then we propose a robust residual generation and evaluation scheme using a post-filter that verifies a particular design objective. This approach is compared with previous results based on the standard Kalman filter and gives better results for sensors fault diagnosis.

The rest of the paper is organized as follows. In Section 2, the quadrotor helicopter attitude dynamics modelled and then controlled using the LQR approach. Section 3 presents the first main result of this paper, which is related to the modelling of networked control systems. Finally, Section 4 we present our second main result concerned with residual generation and evaluation using an adaptive threshold. Simulation results are given in Section 5 and the paper is concluded in Section 6.

2. Description of the quadrotor helicopter dynamics

The mini-helicopter under study has four fixed-pitch rotors mounted at the four ends of a simple cross frame, cf. Fig. 1. The attitude is modelled with the Euler-angle representation, which provides an easier expression for the linearised model. Moreover, this representation is more intuitive. The inertial measurement unit model is given with the quaternion representation of the attitude. This choice is governed by the implementation of the attitude observer, which will be easier with the quaternion parametrization of the attitude.

Fig. 1. Quadrotor mini-helicopter.

2.1. Quadrotor model. The quadrotor is a small aerial vehicle controlled by the rotational speed of four blades, driven by four electric motors. A quadrotor is considered to be a VTOL (vertical take off and landing) vehicle able to hover. Two frames are considered to describe the dynamic equations: the inertial frame $N(e_{x_n}, e_{y_n}, e_{z_n})$ and the body frame $B(e_{x_b}, e_{y_b}, e_{z_b})$ attached to the UAV with its origin at the centre of mass of the vehicle.

The quadrotor orientation can be parametrized by three rotation angles with respect to frame N: yaw (Ψ), pitch (Θ) and roll (Φ). $\omega \in \mathbb{R}^3$ is the angular velocity of the quadrotor relative to N expressed in B. The quadrotor is controlled by independently varying the rotational speed ω_{mi}, $i = 1, \ldots, 4$, of each electric motor. The force f_i and the relative torque Q_i produced by motor i are proportional to ω_{mi},

$$f_i = b\omega_{mi}^2, \qquad (1)$$

$$Q_i = k\omega_{mi}^2, \qquad (2)$$

where $k > 0$, $b > 0$ are two parameters depending on the density of air, the radius, the shape, the pitch angle of the blade and other factors. The three torques that constitute the control vector for the quadrotor are expressed in frame B as

$$\tau_a^\phi = d(f_2 - f_4), \qquad (3)$$

$$\tau_a^\theta = d(f_1 - f_3), \qquad (4)$$

$$\tau_a^\psi = Q_1 + Q_3 - Q_2 - Q_4, \qquad (5)$$

where d represents the distance from one rotor to the centre of mass of the quadrotor. From the Newton–Euler approach, the kinematic and dynamic equations of the quadrotor are given by

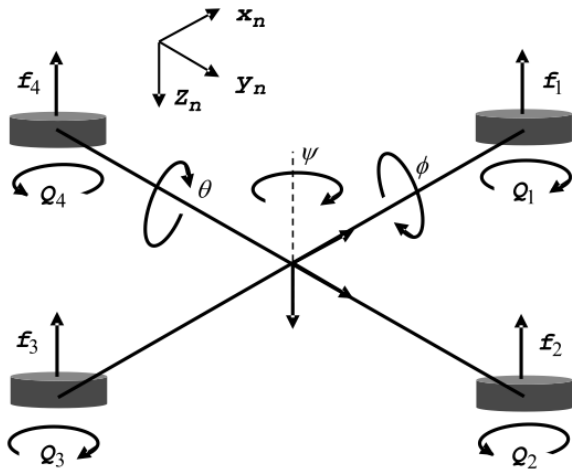$$(\dot{\phi}, \dot{\theta}, \dot{\psi}) = M\omega, \qquad (6)$$

Fig. 2. Quadrator mini-helicopter configuration: the inertial frame $N(e_{x_n}, e_{y_n}, e_{z_n})$ and the body frame $B(e_{x_b}, e_{y_b}, e_{z_b})$.

$$I_f\dot{\omega} = -\omega \times I_f\omega + \tau_a + G_a, \qquad (7)$$

where $I_f \in \mathbb{R}^{3\times3}$ represents the constant inertial matrix expressed in B (i.e. $I_f = \text{diag}(I_{fx}, I_{fy}, I_{fz})$) and $\times$ in (7) denotes the cross product. The matrix M is given by

$$M = \begin{bmatrix} 1 & \text{tg}\,\theta\sin\phi & \text{tg}\,\theta\cos\phi \\ 0 & \cos\phi & -\sin\phi \\ 0 & \frac{\sin\phi}{\cos\theta} & \frac{\cos\phi}{\cos\theta} \end{bmatrix} \begin{bmatrix} \omega_x \\ \omega_y \\ \omega_z \end{bmatrix}, \qquad (8)$$

where $\omega_x, \omega_y, \omega_z$ are the three measurements from tri-axe rate gyros. Due to the rotation combination of the quadrotor four rotors, the gyroscopic torques G_a are given as follows:

$$G_a = \sum_{i=1}^{4} I_r(\omega \times e_{z_b})(-1)^{i+1}\omega_{mi}, \qquad (9)$$

where I_r is the inertia of the so-called rotor (composed of the motor rotor itself, the shape and the gears). A linear control law that stabilizes the system described by the non-linear model ((6) and (7)) around the hover conditions is designed.

Note that non-linearities are second order. Therefore, it is reasonable to consider a linear approximation. From (6) and (7) and under the hover condition ($\phi \approx \theta \approx \psi \approx 0$), we can write

$$(\dot{\phi}, \dot{\theta}, \dot{\psi})^T = (\omega_1, \omega_2, \omega_3)^T. \qquad (10)$$

Then the dynamical model is obtained in terms of Euler angles,

$$\ddot{\phi} = \dot{\theta}\dot{\psi}\frac{I_{fy} - I_{fz}}{I_{fx}} + \frac{\tau_a^\phi}{I_{fx}}, \qquad (11)$$

$$\ddot{\theta} = \dot{\phi}\dot{\psi}\frac{I_{fz} - I_{fx}}{I_{fy}} + \frac{\tau_a^\theta}{I_{fy}}, \qquad (12)$$

$$\ddot{\psi} = \dot{\phi}\dot{\theta}\frac{I_{fx} - I_{fy}}{I_{fz}} + \frac{\tau_a^\psi}{I_{fz}}. \qquad (13)$$

The gyroscopic torques G_a are not considered for the design of the control law. However, they are taken into account in simulations in order to analyse the robustness features.

2.2. Attitude control. In this section, the linearised model of (6) and (7) is first derived. Then a control law is briefly summarized. Note that this paper is not dedicated to the design of a particular control law (Tayebi and McGilvray, 2006; Castellanos *et al.*, 2005). Therefore, we use a simple LQ controller for stabilizing the quadrotor system. For the state feedback we use an estimated state provided by an extended Kalman filter that estimates both the system state and the network-induced delay.

The linear dynamics of the system described before are given by the following state space model:

$$x^T = (\phi, \dot{\phi}, \theta, \dot{\theta}, \psi, \dot{\psi}). \qquad (14)$$

The system (12) around the hover conditions is given by

$$\dot{x}_t = Ax_t + Bu_t, \qquad (15)$$

where

$$A = \begin{bmatrix} A_0 & 0 & 0 \\ 0 & A_0 & 0 \\ 0 & 0 & A_0 \end{bmatrix}, \qquad B = \begin{bmatrix} B_x & 0 & 0 \\ 0 & B_y & 0 \\ 0 & 0 & B_z \end{bmatrix},$$

$$A_0 = \begin{bmatrix} 0 & 1 \\ 0 & 0 \end{bmatrix}, \qquad B_i = \begin{bmatrix} 0 \\ \frac{1}{I_{fi}} \end{bmatrix}.$$

The attitude stabilization problem consists in driving the quadrotor attitude from any initial condition to a desired constant orientation and maintaining it thereafter. As a consequence, the angular velocity vector is also brought to zero and remains null once the desired attitude is reached, $x \mapsto 0$, $t \mapsto \infty$. The discrete linear controller is given by

$$u_{kh} = -Lx_{kh}. \qquad (16)$$

The control is designed to minimize to following objective function:

$$J = \sum_{k=0}^{N-1} [x_k^T Q_d x_k + u_k^T R_d u_k] + x_N^T Q_0 x_N, \qquad (17)$$

where

$$\Phi = e^{Ah}, \quad \Gamma = \int_{kh}^{(k+1)h} e^{As} B \, \mathrm{d}s$$

$$Q_d = \int_{kh}^{(k+1)h} \Phi^T(s) Q \Phi(s) \, \mathrm{d}s$$

and

$$R_d = \int_{kh}^{(k+1)h} (\Gamma^T(s) Q \Gamma(s) + R) \, \mathrm{d}s$$

where matrices Q, R are symmetric and positive definite.

Furthermore, the following assumptions are taken into account.

Assumption 1. The full state vector is available (angles and angular velocities). In practice, these state variables are obtained from the measurements of rate gyros, accelerometers and magnetometers by using a dedicated attitude observer (Castellanos *et al.*, 2005).

Assumption 2. A periodic sampling is used.

Assumption 3. The control signals remain constant between two updates.

Proposition 1. *Consider the quadrotor rotational dynamics described by (12). Then, the discrete control is given by*

$$u_{kh} = \begin{bmatrix} \tau_{a,kh}^{\phi} & \tau_{a,kh}^{\theta} & \tau_{a,kh}^{\psi} \end{bmatrix} = -Lx_{kh}. \qquad (18)$$

2.3. Control simulation. The weighting matrices Q and R are chosen in order to obtain a suitable transient response, and only feasible control signals are applied to the actuators. Then for a sampling time $h = 0.01$ s the matrix gain which minimizes (17) and locally stabilizes the quadrotor at $x = 0$ is given by

$$L = \begin{bmatrix} 0.0352 & 0 & 0 \\ 0.0284 & 0 & 0 \\ 0 & 0.0352 & 0 \\ 0 & 0.0284 & 0 \\ 0 & 0 & 0.0352 \\ 0 & 0 & 0.0284 \end{bmatrix}.$$

Here we simply present some results of the drone attitude simulation with a variable step response (Fig. 3) and the LQ controller signal (Fig. 4).

3. Model for NCSs under the fault effect and communication delay

Induced time delays in networked controlled systems can become a source of instability and degradation of control performance (Yi *et al.*, 2007; Zhang *et al.*, 2004; Xiong and Lam, 2007; Sahebsara *et al.*, 2007). When the system is controlled over a network, we have to take into account the sensor to controller delays and controller to actuator delays. Note that delays, in general, cannot be considered constant and known. Network-induced delays may vary, depending on the network traffic, medium access protocol and the hardware.

Assumption 4. For data acquisition it is supposed that the sensor is time-driven and the sampling period is denoted by h. Both the controller and the actuator are
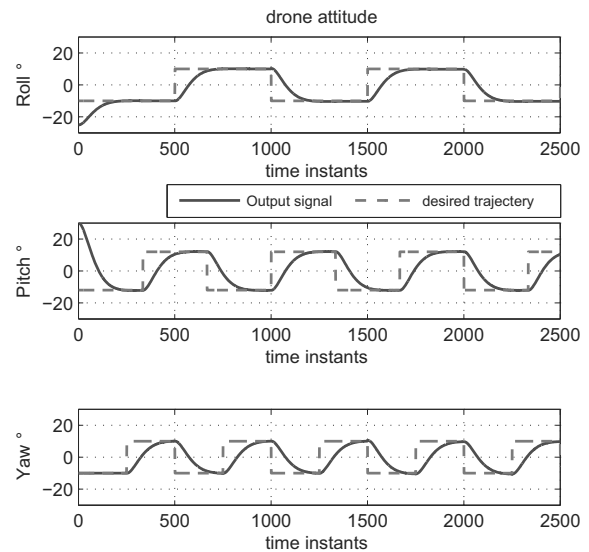

Fig. 3. Quadrotor attitude (φ, θ, ψ) and reference.

event-driven. This signifies that calculation of the new control or actuator signal is started as soon as the new control or actuator information arrives, as illustrated in Fig. 5

Assumption 5. Unknown time-varying network-induced delay at time step k is denoted by τ_k, and $\tau_k = \tau_k^{sc} + \tau_k^{ca}$ is smaller than one sampling period $\tau_k \leq h$, τ_k^{sc} and τ_k^{ca} are the sensor-to-controller delay and the controller-to-actuator delay, respectively. There is no packet dropout in the networks. Thus, the control input (zero-order hold assumed) over a sampling interval $[kh, (k+1)h]$ is

$$u_t = \begin{cases} u_{k-1}, & t \in [kh, kh + \tau_k], \\ u_k, & t \in [kh + \tau_k, (k+1)h]. \end{cases} \quad (19)$$

Let us first assume that the residual generation and evaluation algorithms are executed instantaneously at every sampling period k. Based on this assumption, if the control input is kept constant over each sampling interval h and if we consider that fault inputs have slow dynamics, the discrete time system can be described by

$$\begin{cases} x_{k+1} & = \Phi\, x_k + \Gamma_{0,\tau_k}\, u_k + \Gamma_{1,\tau_k}\, u_{k-1}, \\ y_k & = C x_k + v_k. \end{cases} \quad (20)$$

From

$$\Gamma_{0,\tau_k} = \int\limits_0^{h-\tau_k} e^{As} B\, \mathrm{d}s,$$

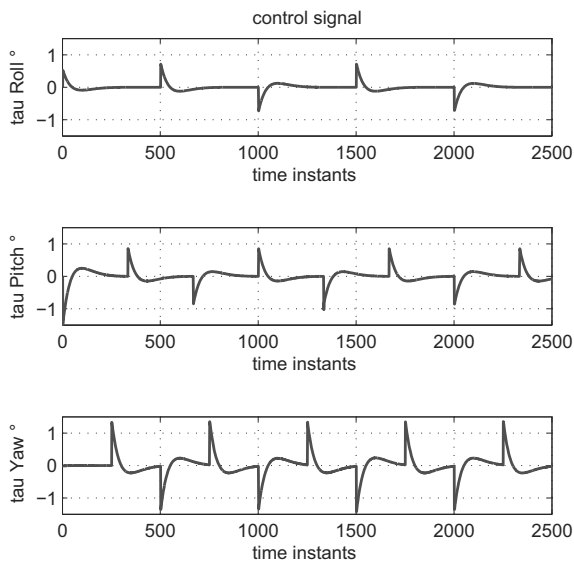$$\Gamma_{1,\tau_k} = \int\limits_{h-\tau_k}^h e^{As} B\, \mathrm{d}s$$

it follows that

$$\Gamma = \int\limits_0^h e^{As} B\, \mathrm{d}s = \Gamma_{0,\tau_k} + \Gamma_{1,\tau_k}$$

and hence $\Gamma_{0,\tau_k} = \Gamma - \Gamma_{1,\tau_k}$.

In accordance with the properties of the definite integral, if we introduce the control increment Δu_k, the plant (20) with an unknown disturbance vector and a fault vector, which must be detected, is described by

$$\begin{cases} x_{k+1} & = \Phi\, x_k + \Gamma\, u_k + \Gamma_{1,\tau_k}\, \Delta u_k \\ & \quad + \Xi_x d_k + \Psi_x f_k, \\ y_k & = C x_k + \Xi_y d_k + \Psi_y f_k, \end{cases} \quad (21)$$

where $f_k \in \mathbb{R}^q$ is the fault vector and $d_k \in \mathbb{R}^p$ is the noise vector.

Remark 1. Adding the sensor fault effect in both process and observation equations (21) is for the generalisation of the study. In our application which considers only sensor faults we take $\Psi_x = 0$.

The matrix A is called diagonalizable if there exists an invertible matrix P such that

$$A = P\Lambda P^{-1} = P\mathrm{diag}(\lambda_1, \lambda_2, \ldots, \lambda_n)P^{-1}, \quad (22)$$

where $\lambda_1, \lambda_2, \ldots, \lambda_n$ are the eigenvalues of the matrix A. Then we can write

$$e^{At} = I + At + \cdots + \frac{1}{n}A^n t^n \quad (23)$$

$$= PP^{-1} + P\Lambda P^{-1}t + \cdots + \frac{1}{n}(P\Lambda P^{-1})^n t^n \quad (24)$$

$$= P(I + \Lambda t + \cdots + \frac{1}{n}\Lambda^n t^n)P^{-1} \quad (25)$$
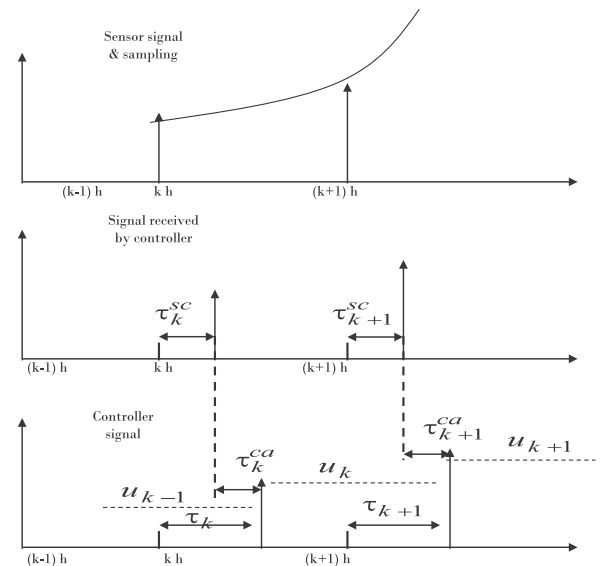
$$= Pe^{\Lambda t}P^{-1}. \quad (26)$$

Fig. 4. Control signal.

Fig. 5. Timing diagram for data communication.

From Eqn. (21), we can write

$$\Gamma_{1,\tau_k}\,\Delta u_k$$

$$= \int_{h-\tau_k}^{h} P\,e^{\Lambda s}P^{-1}\,B\,\mathrm{d}s\,\Delta u_k \tag{27}$$

$$= P\int_{h-\tau_k}^{h} e^{\Lambda s}\,\mathrm{d}s\,P^{-1}B\,\Delta u_k \tag{28}$$

$$= P\begin{bmatrix}\displaystyle\int_{h-\tau_k}^{h} e^{\lambda_1 s}\,\mathrm{d}s & 0 & \cdots & 0 \\ 0 & \ddots & \ddots & \vdots \\ \vdots & \ddots & \ddots & 0 \\ 0 & \cdots & 0 & \displaystyle\int_{h-\tau_k}^{h} e^{\lambda_n s}\,\mathrm{d}s\end{bmatrix}$$

$$\times\, P^{-1}B\,\Delta u_k \tag{29}$$

$$= P\begin{bmatrix}\frac{1}{\lambda_1}e^{\lambda_1 h} & 0 & \cdots & 0 \\ 0 & \ddots & \ddots & \vdots \\ \vdots & \ddots & \ddots & 0 \\ 0 & \cdots & 0 & \frac{1}{\lambda_n}e^{\lambda_n h}\end{bmatrix}P^{-1}B\,\Delta u_k$$

$$-\, P\begin{bmatrix}\frac{1}{\lambda_1}e^{\lambda_1 (h-\tau_k)} & 0 & \cdots & 0 \\ 0 & \ddots & \ddots & \vdots \\ \vdots & \ddots & \ddots & 0 \\ 0 & \cdots & 0 & \frac{1}{\lambda_n}e^{\lambda_n (h-\tau_k)}\end{bmatrix} \tag{30}$$

$$\times\, P^{-1}B\,\Delta u_k \tag{31}$$

$$= \Gamma_\Delta\,\Delta u_k - P\,\mathrm{diag}\left[\frac{1}{\lambda_1},\ldots,\frac{1}{\lambda_n}\right]\mathrm{diag}(\beta_k)$$

$$\times\begin{bmatrix}e^{\lambda_1(h-\tau_k)} \\ e^{\lambda_2(h-\tau_k)} \\ \vdots \\ e^{\lambda_n(h-\tau_k)}\end{bmatrix} \tag{32}$$

$$= \Gamma_\Delta\,\Delta u_k - \Gamma_{\Delta,k}\begin{bmatrix}e^{\lambda_1(h-\tau_k)} \\ e^{\lambda_2(h-\tau_k)} \\ \vdots \\ e^{\lambda_n(h-\tau_k)}\end{bmatrix}$$

$$= \Gamma_\Delta\,\Delta u_k - \Gamma_{\Delta,k}\,d_{\tau_k} \tag{33}$$

with

$$\beta_k = [\beta_k^1\,\beta_k^2\,\ldots\,\beta_k^n]^T = P^{-1}B\Delta u_k \in \mathbb{R}^{n,1},$$

$$\mathrm{diag}(\beta_k) = \begin{bmatrix}\beta_k^1 & 0 & \cdots & 0 \\ 0 & \beta_k^2 & \ddots & \vdots \\ \vdots & \ddots & \ddots & 0 \\ 0 & \cdots & 0 & \beta_k^n\end{bmatrix},$$

$$\Gamma_\Delta = P\begin{bmatrix}\frac{1}{\lambda_1}e^{\lambda_1 h} & 0 & \cdots & 0 \\ 0 & \ddots & \ddots & \vdots \\ \vdots & \ddots & \ddots & 0 \\ 0 & \cdots & 0 & \frac{1}{\lambda_n}e^{\lambda_n h}\end{bmatrix},$$

$$\Gamma_{\Delta,k} = P\,\mathrm{diag}\left[\frac{1}{\lambda_1}\ \ \frac{1}{\lambda_2}\ \ \cdots\ \ \frac{1}{\lambda_n}\right]\mathrm{diag}(\beta_k).$$

According to (32), the model of (21) can also be rewritten as

$$\begin{cases}x_{k+1} &= \Phi\,x_k + \Gamma\,u_k + \Gamma_\Delta\,\Delta u_k - \Gamma_{\Delta k}d_{\tau k} \\ & \quad + \Xi_x d_k + \Psi_x f_k, \\ y_k &= Cx_k + \Xi_y d_k + \Psi_y f_k\end{cases} \tag{34}$$

by defining

$$\Gamma_k^a = \begin{bmatrix}\Gamma \\ \Gamma_\Delta\end{bmatrix}, \quad u_k^a = \begin{bmatrix}u_k \\ \Delta u_k\end{bmatrix}, \quad \Xi_{x,k}^a = \begin{bmatrix}\Xi_x \\ -\Gamma_{\Delta k}\end{bmatrix},$$

$$\Xi_y^a = \begin{bmatrix}\Xi_y \\ 0\end{bmatrix}, \quad d_k^a = \begin{bmatrix}d_k \\ d_{\tau,k}\end{bmatrix},$$

which results in

$$\begin{cases}x_{k+1} &= \Phi x_k + \Gamma_k^a u_k^a + \Xi_{x,k}^a d_k^a + \Psi_x f_k, \\ y_k &= Cx_k + \Xi_y^a d_k^a + \Psi_y f_k.\end{cases} \tag{35}$$

In a practical situation, ensuring the residual generator robustness against unknown input disturbances is considered the main issue of FDI algorithm design. In the case of structured types of uncertainties, the existing literature provides a wide variety of solutions for achieving robustness (see, for instance, Chen and Patton, 1999; Ding, 2008). In the next section, FDI is revisited, considering network-induced effects. Model based fault detection relies on the generation of a residual signal which is sensitive to failures and able to decouple faults from other unknown disturbance inputs. The design must ensure that residuals are closed to zero in a failure-free case while clearly deviating from zero in the presence of faults. In a first attempt, the idea is to consider a residual generator based on the following state observer:

$$\begin{cases}\hat{x}_{k+1} &= \Phi\hat{x}_k + \Gamma_k^a u_k^a + L(y_k - \hat{y}_k), \\ y_k &= C\hat{x}_k.\end{cases} \tag{36}$$

The residual generator is given by

$$r_k = T(y_k - \hat{y}_k), \tag{37}$$

where L and T are matrices designed to fulfil fault detection and isolation requirements. From (36) and (37), it results that the estimation error $\varepsilon_k = x_k - \hat{x}_k$ propagates as follows:

$$\varepsilon_{k+1} = (\Phi - LC)\varepsilon_k + (\Xi_{x,k}^a - L\Xi_y^a)d_k^a$$
$$+ (\Psi_x - L\Psi_y)f_k. \tag{38}$$

The observer gain L is designed to stabilize the matrix $(\Phi - LC)$.

After the application of the $\mathcal{Z}$-*transformation*, we obtain the following transfer function model:

$$z_k = T(C(zI - \Phi + LC)^{-1}(\Xi^a_{x,k} - L\Xi^a_y) + \Xi^a_y)d^a_k$$
$$+ T(C(zI - \Phi + LC)^{-1}(\Psi_x - L\Psi_y) + \Psi_y)f_k. \quad (39)$$

The matrix parameters T and L are determined to verify the following requirements:

- asymptotic stability under fault free conditions, i.e., $f_k = 0$,

- minimization of disturbance effects,

- maximization of fault effects.

Perfect fault detection means the total decoupling of the residual signal from unknown inputs. This can be described by

$$T(C(zI - \Phi + LC)^{-1}(\Xi^a_{x,k} - L\Xi^a_y) + \Xi^a_y)d^a_k = 0,$$
$$T(C(zI - \Phi + LC)^{-1}(\Psi_x - L\Psi_y) + \Psi_y)f_k \neq 0. \quad (40)$$

Actually, there are various approaches (Gertler, 1998; Chen and Patton, 1999; Frank and Ding, 1997; Ding, 2008) to the design for the gain matrices L and T. Therefore, developing a new technique does not make the main objective of this paper. In the remainder of the paper, we suppose that the system is controlled over a communication network. Thus, we take in consideration the sensor to controller delay and the controller to actuator delay in our design. For the illustration of FDI performance degradation under a delay constraint, we perform a simulation using the system described by (15) as a plant model. It is supposed that the FD system based on standard Kalman filtering is connected to the plant via a network.

For this simulation, the network delay is supposed to be a Gaussian variable, the fault associated to the first attitude sensor (ϕ: Roll) occurs at time instant $k = 1000$ and the fault associated to the second attitude sensor (ψ: Yaw) occurs at time instant $k = 1500$. The result shown in Fig. 7 does not allow us to distinguish between the fault and the network variable delay effects. Hence, it appears that the robustness of the fault diagnosis system against network-induced delays depends on the amplitude of the unknown term $\Gamma_{\Delta,k}$, $d_{\tau,k}$.

It is clear that any robust design has to decouple or at least minimize the effect of delay on the residual. This problem is equivalent to fault detection under the effect of Gaussian noise and unknown inputs at the same time (Darouach *et al.*, 2003). The delay effect can

be considered an unknown input with a time-varying distribution matrix $\Gamma_{\Delta,k}$. In the sequel, we use a robust filter for detection of faults that may occur in the quadrotor system.

4. Robust residual generation and evaluation

The objective of fault diagnosis is to perform two main decision tasks (Frank and Ding, 1997): fault detection, consisting in deciding whether or not a fault has occurred, and fault isolation, consisting in deciding which element of the system has failed. The general procedure comprises the following two steps:

- Residual generation: the process of associating, with the pair model–observation, features that allow evaluating the difference with respect to normal operating conditions.

- Residual evaluation: the process of comparing residuals with some predefined thresholds according to a test and at a stage where symptoms are produced.

This implies designing residuals that are close to zero in fault-free situations while clearly deviating from zero in the presence of faults, and possess the ability to discriminate between all possible modes of faults, which explains the use of the term isolation. Therefore, the objective here is to design a residual generator similar to the one given by Eqn. (37) with the additional propriety of robustness against network delay effects. Several approaches have been proposed in the literature (Wang *et al.*, 2009; Sauter *et al.*, 2009; Chabir *et al.*, 2008).
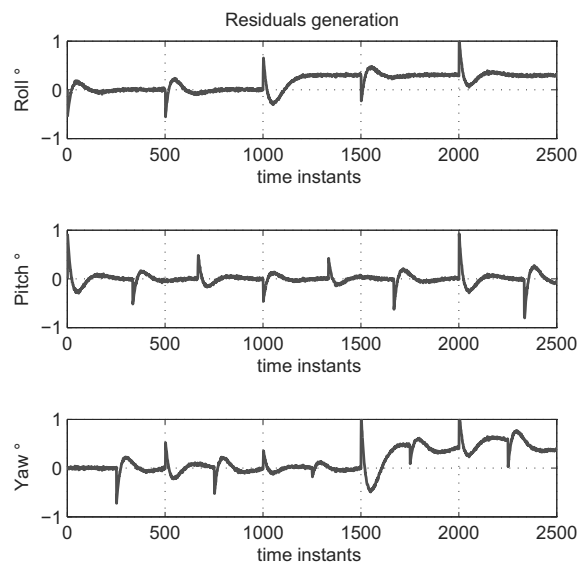

Fig. 6. Residuals generation by the standard Kalman filter (Chabir *et al.*, 2010).

4.1. Residual generation. A solution of the above mentioned problem towards the design of an observer based residual generator will be derived. First, let us define the vector

$$z_k = \begin{bmatrix} x_k \\ e_k \end{bmatrix}. \tag{41}$$

The overall system dynamics, which include the plant and the residual generator, can be expressed as

$$\begin{cases} z_{k+1} &= \bar{A}z_k + \bar{B}u_k^a + \bar{\Xi}_{k,x}d_k^a + \bar{\Psi}_x f_k \\ r_k &= T\bar{C}z_k + T\Xi_y^a d_k^a + T\Psi_y f_k, \end{cases} \tag{42}$$

where

$$\bar{A} = \begin{bmatrix} \Phi & 0 \\ 0 & \Phi - K_k C \end{bmatrix},$$

$$\bar{C} = \begin{bmatrix} 0 & C \end{bmatrix}, \qquad \bar{C} = \begin{bmatrix} \Gamma_k^a \\ 0 \end{bmatrix},$$

$$\bar{\Xi}_{k,x} = \begin{bmatrix} \Xi_{k,x}^a \\ \Xi_{k,x}^a - L\Xi_y^a \end{bmatrix}, \qquad \bar{\Psi}_x = \begin{bmatrix} \Psi_x \\ \Psi_x - L\Psi_y \end{bmatrix}.$$

It is assumed that the plant is mean square stable, since the observer gain matrix L has no influence on the system in (42). The overall system dynamics (plant + residual generator) is mean square stable. The post-filter T and the observer gain matrix L are the design parameters for the residual generator. The main objective of the design of the residual generator is to improve the sensitivity of the FD system to faults while keeping robustness against disturbances. Thus, the selection of the design parameters L and T can be formulated as the following optimization problem:

$$\sup \mathcal{J} = \sup_{L,T} \frac{\| G_z^{rf} \|_-}{\| G_z^{rd} \|_\infty}, \tag{43}$$

where

$$G_z^{rd} = T\bar{C}\left(zI - \bar{A} + L\bar{C}\right)^{-1}\bar{\Xi}_{k,x} + T\Xi_y^a, \tag{44}$$

$$G_z^{rf} = T\bar{C}\left(zI - \bar{A} + L\bar{C}\right)^{-1}\bar{\Psi}_x + T\Psi_y. \tag{45}$$

4.2. Residual evaluation. The second step of the fault detection procedure is to evaluate the residual. Residual evaluation is an important step of model based FD approach (see, for instance, Ding, 2008). This step includes the calculation of the residual evaluation function and determination of the detection threshold. The decision for successful fault detection is based on the comparison between the results obtained from the residual evaluation function and the determined threshold. The following residual evaluation function is proposed:

$$\begin{aligned} J_k^e &= \| r_k \|_{2,N} \\ &= \sqrt{\left(\frac{1}{N}\sum_{i=1}^{N} r_{k-i}\right)^T \left(\frac{1}{N}\sum_{i=1}^{N} r_{k-i}\right)}, \end{aligned} \tag{46}$$

where N is the length of the evaluation window. The variance of the residual signal can be expressed as

$$\sigma_{rk} = \mathrm{E}\left((r_k - \bar{r}_k)^T (r_k - \bar{r}_k)\right). \tag{47}$$

Under the assumption that the unknown input and control input are $\mathcal{L}_2$ bounded, the following theorem can be given.

Theorem 1. *Given the system (15) and the constants $\gamma_1 > 0$, $\gamma_2 > 0$, the following equation holds true:*

$$\begin{aligned} \sigma_{rk} &= \mathrm{E}\left((r_k - \bar{r}_k)^T (r_k - \bar{r}_k)\right) \\ &< \gamma_1 \sum_{j=0}^{k} \left(v_j^T v_j + \Delta u_j^T \Delta u_j\right) \\ &+ \gamma_2 \left(v_k^T v_k + \Delta u_k^T \Delta u_k\right) \end{aligned} \tag{48}$$

if there exist $P > 0$ such that

$$\begin{bmatrix} -P & P\bar{A} & P\bar{B} & \breve{\Xi}_{k,x} \\ (\star) & -P & 0 & 0 \\ (\star) & (\star) & -I & 0 \\ (\star) & (\star) & (\star) & -I \end{bmatrix} < 0, \tag{49}$$

$$\begin{bmatrix} -P & \bar{C} \\ (\star) & -\gamma_1 I \end{bmatrix} < 0, \tag{50}$$

$$\begin{bmatrix} -I & \Psi_y \\ (\star) & -\gamma_2 I \end{bmatrix} < 0, \tag{51}$$

where the symbols $(\star)$ denote the symmetric terms

$$\breve{\Xi}_{k,x} = \begin{bmatrix} \bar{\Xi}_{x,k}^a \\ \bar{\Xi}_{x,k}^a - L\Xi_y^a \end{bmatrix}, \quad \breve{\Xi}_{x,k}^a = [\Xi_x, -\bar{\Gamma}_{\Delta,k}],$$

and $\bar{\Gamma}_{\Delta,k}$ is calculated for $\Delta u = \max(\Delta u)$.

Proof. Define the following Lyapunov function candidate:

$$V_k = z_k^T P z_k$$

with $P > 0$ and $V_0 = 0$. This equation satisfies

$$E\{V_{k+1}\} - E\{V_k\} < \sum_{j=0}^{k-1} (d_j^{aT} d_j^a).$$

It follows that

$$\begin{aligned} E\{V_k\} &= E\{z_k^T P z_k\} \\ &= \tilde{z}_k^T P \tilde{z}_k + E\left\{(z_k - \tilde{z}_k)^T (z_k - \tilde{z}_k)\right\} \\ &= \tilde{z}_k^T P \tilde{z}_k + \mathrm{trace}(P\sigma_z), \end{aligned}$$

where $\sigma_z = E\left\{(z_k - \tilde{z}_k)\right\}$.

By evaluating $E\{v_{k+1}\}$, we get

$$
\begin{aligned}
E\{V_{k+1}\} &= E\{z_{k+1}^T P z_{k+1}\} \\
&= E\{(\bar{A}z_k + \bar{B}\bar{u}_k^a + \bar{\Xi}_{k,x} d_k^a)^T \\
&\quad \times P (\bar{A}z_k + \bar{B}\bar{u}_k^a + \bar{\Xi}_{k,x} d_k^a)\} \\
&= E\left[\begin{array}{ccc} \tilde{z}_k & \bar{u}_k^a & d_k^a \end{array} \right] M_{1,0} \left[\begin{array}{ccc} \tilde{z}_k & \bar{u}_k^a & d_k^a \end{array} \right]^T \\
&\quad + \left[\begin{array}{ccc} \tilde{z}_k & \bar{u}_k^a & d_k^a \end{array} \right] M_{1,1} \left[\begin{array}{ccc} \tilde{z}_k & \bar{u}_k^a & d_k^a \end{array} \right] \\
&\quad + \text{trace}(\sigma_z M_A),
\end{aligned}
$$

where

$$
M_{1,0} = \left[\begin{array}{ccc} \bar{A}_0^T & \bar{B}_0^T & \bar{\Xi}_0^T \end{array} \right]^T P \left[\begin{array}{ccc} \bar{A}_0 & \bar{B}_0 & \bar{\Xi}_0 \end{array} \right],
$$

$$
M_{1,1} = \sum_{i=1}^{l} \left(\sigma_i^2 \left[\begin{array}{c} 0 \\ \bar{B}_i^T \\ 0 \end{array} \right] P \left[\begin{array}{ccc} 0 & \bar{B}_i & 0 \end{array} \right] \right),
$$

$$
M_A = \bar{A}_p^T P \bar{A}_p,
$$

such that

$$
\bar{A}_p = \left[\begin{array}{cc} \Phi & 0 \\ 0 & \Phi - \rho_1 LC \end{array} \right], \quad \bar{B}_p = \left[\begin{array}{c} \Gamma_p^a \\ \rho_2 \Gamma_p^a \end{array} \right]
$$

$$
\bar{C}_p = \left[\begin{array}{cc} 0 & \rho_1 C \end{array} \right],
$$

where $p \in \{0, 1\}$ and $M_1 = M_{1,0} + M_{1,1}$.

Suppose that

$$
M_1 < \left[\begin{array}{ccc} P & 0 & 0 \\ 0 & I & 0 \\ 0 & 0 & I \end{array} \right]. \tag{52}
$$

Then

$$
\left[\begin{array}{c} \bar{A}_0^T \\ (\bar{B}_0 + \sigma_1 \bar{B}_1)^T \\ \bar{\Xi}_{x,0}^T \end{array} \right] (P^{-1})^{-1}
$$

$$
\left[\begin{array}{ccc} \bar{A}_0 & (\bar{B}_0 + \sigma_1 \bar{B}_1) & \bar{\Xi}_{x,0} \end{array} \right]
$$

$$
- \left[\begin{array}{ccc} P & 0 & 0 \\ 0 & I & 0 \\ 0 & 0 & I \end{array} \right] < 0 \tag{53}
$$

and hence

$$
M_A < P. \tag{54}
$$

By using the Schur complement, we get

$$
\left[\begin{array}{cccc} -P^{-1} & \bar{A}_0 & (\bar{B}_0 + \sigma_1 \bar{B}_1) & \bar{\Xi}_{x,0} \\ (\star) & -P & 0 & 0 \\ (\star) & (\star) & -I & 0 \\ (\star) & (\star) & (\star) & -I \end{array} \right] < 0.
$$

Equivalently,

$$
\left[\begin{array}{cccc} -P & P\bar{A}_0 & P(\bar{B}_0 + \sigma_1 \bar{B}_1) & P\bar{\Xi}_{x,0} \\ (\star) & -P & 0 & 0 \\ (\star) & (\star) & -I & 0 \\ (\star) & (\star) & (\star) & -I \end{array} \right] < 0.
$$

Note that the LMI given in (53) implies (54). From (53), (54), it is evident that

$$
E\{V_{k+1}\} < E\{V_k\} + (d_k^{a\,T} d_k^a + \bar{u}_k^{a\,T} \bar{u}_k^a). \tag{55}
$$

This leads to

$$
\tilde{z}_k^T P \tilde{z}_k + \text{trace}(P\sigma_z) < \left\{ \sum_{j=0}^{k-1} (d_j^{aT} d_j^a + \bar{u}_j^{a\,T} \bar{u}_j^a) \right\}.
$$

Now, from (48), we get

$$
\begin{aligned}
\sigma_{rk} &= E\left\{ (r_{k+1} - \bar{r}_{k+1})^T (r_{k+1} - \bar{r}_{k+1}) \right\} \\
&= \left[\begin{array}{ccc} \tilde{z}_k & \bar{u}_k^a & d_k^a \end{array} \right] M_1 \left[\begin{array}{c} \tilde{z}_k \\ \bar{u}_k^a \\ d_k^a \end{array} \right] + \text{trace}(\sigma_z M_c),
\end{aligned}
$$

where $M_c = (\rho_1 C)^T (\rho_1 C) = \rho_1^2 C^T C$.

If

$$
\sigma_{rk} < V_k \Leftrightarrow \text{trace}(\sigma_z M_c) < \tilde{z}_k^T P \tilde{z}_k + \text{trace}(P\sigma_z),
$$

then it is evident that

$$
\begin{aligned}
\sigma_{rk} &< \gamma_1 E\left\{ \sum_{j=0}^{k-1} (d_j^{aT} d_j^a + \bar{u}_j^{a\,T} \bar{u}_j^a) \right\} \\
&\quad + \gamma_2 E\{d_k^{aT} d_k^a\} + \gamma_2 E\left\{ \bar{u}_k^{a\,T} \bar{u}_k^a \right\}
\end{aligned}
$$

Using the Schur complement, we get

$$
M_c < \gamma_1 P \Leftrightarrow \frac{1}{\gamma_1} \rho_1^2 C^T C - P < 0,
$$

$$
M_1 < \gamma_2 \Leftrightarrow \frac{1}{\gamma_2} \rho_1^2 C^T C - P < 0.
$$

This concludes the proof. ∎

Note that Δu_k is set to the allowed upper bound of the control input $\max(\Delta u_k)$. The threshold can be set as

$$
J_k^{th} = \sqrt{\alpha_N \beta}, \tag{56}
$$

where

$$
\beta = \sup \sigma_{rk}
$$

$$
= \gamma_1 (\delta_{d,2} + \sum_{j=0}^{k} (\Delta u_j^T \Delta u_j)) \tag{57}
$$

$$
+ \gamma_2 (\delta_{d,\infty} + \Delta u_k^T \Delta u_k) \tag{58}
$$

such that

$$
\delta_{d,2} \geq \sum_{j=0}^{k} (v_j^T v_j), \delta_{d,\infty} \geq v_k^T v_k
$$

are the $\mathcal{L}_2$, and $\mathcal{L}_\infty$ norm of the unknown input, respectively. The parameter $0 < \alpha_N < 1$ is a constant

value that depends on the length of the evaluation window N. The constants γ_1 and γ_2 are parameters that represent the bounds on the variance of the residual signal. Note that since the residual signal is a white noise process, the threshold will depend on the statistical part of it (which means the variance of the residual signal). After the determination of a threshold, a decision whether a fault occurs has to be made. The decision logic for the FD system can be defined as follows: $J_k^e > J_k^{th} \Rightarrow$ fault, $J_k^e < J_k^{th} \Rightarrow$ no fault. The threshold J_k^{th} is adaptive and is influenced by Δu_k, which has to be calculated online. The simulations in the next section are performed in order to validate the results of the proposed residual evaluator.

5. Simulation

The upper bounds on the unknown inputs are $\delta_{d,2} = 0.15$ and $\delta_{d,\infty} = 0.28$. The length of the evaluation window is set to 50 and α_N is set to 0.3. The parameters of the threshold (bounds on the variance of residual) are computed as $\gamma_1 = 0.0058$ and $\gamma_2 = 0.05$. The threshold is then to be determined (adaptively) on-line during the simulation. From the result shown in Fig. 7, it is clear that the adaptive threshold allows fault detection and the likelihood of the false alarm rate is drastically minimized.

6. Conclusion

In this paper we deal with the residual generation and evaluation issue within the framework of networked control systems. The problems addressed in this paper include (i) robustness against network delays as well as noise and (ii) reducing the false alarm rate. In this context, a quadrotor attitude sensor fault is detected by a post-filter
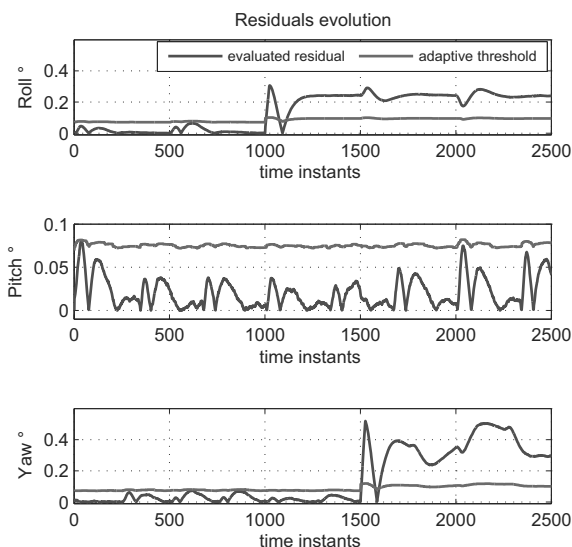
and compared with an adaptive threshold that considers the variation of control inputs as well as unknown inputs. The problem of threshold design is established in terms of linear matrix inequalities. Validation results show the effectiveness of the obtained results.

Fig. 7. Evaluated residual.

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