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Sensor Anomaly Detection and Recovery in the Roll Dynamics of a Delta-Wing Aircraft via Monte Carlo and Maximum Likelihood Methods ⋆

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Abstract: This paper studies the problem of sensor anomaly detection, estimation and recovery for the roll dynamic model of a generic delta-wing aircraft. The proposed algorithm employs particle filtering and maximum likelihood methods to detect and estimate the anomaly. The estimated anomaly is then used to correct the sensor readings. It is assumed that both the system model and sensor outputs are corrupted by noise, which are not necessarily Gaussian. Simulation results are presented to show the performance of the proposed algorithm.

1. INTRODUCTION

Fault detection and recovery techniques are attractive algorithms for practitioners implementing control and estimation algorithms in critical infrastructure, and such methods have attracted considerable research interest; see e.g. the survey papers Isermann (1984); Hwang et al. (2010); Samy et al. (2011); Chen and Patton (2012). Observer-based fault detection techniques are among the most common approaches used for fault detection; see Hwang et al. (2010); Chen and Patton (2012). The basic concept underlying observer-based fault detection techniques is the generation of a residual (or innovation) sequence and the use of a threshold function. One is then typically interested in false-alarm and missed detection rates etc., under particular modelling and uncertainty/noise assumptions.

Early detection of faults, anomalous behaviour and/or attacks are critical to establish a reliable and safe flight operation, and therefore fault detection and fault-tolerant control methods applied to aircraft flight control have received considerable attention. The literature on fault-tolerant control and fault-detection covers manned aircraft (see Brière and Traverse, 1993; Edwards et al., 2010), autonomous fixed wing UAVs (see Cork and Walker, 2007; Bateman et al., 2011; Kwon et al., 2014) and helicopters (see Heredia et al., 2008). Indeed, the literature here is too broad to cover adequately; see the short bibliography and the references therein: Patton (1991); Saif and Guan (1993); Brière and Traverse (1993); De Persis et al. (2001); Marcos et al. (2005); Kobayashi and Simon (2007); Alwi and Edwards (2008); Edwards et al. (2010); Alcorta-Garcia et al. (2011); Shen et al. (2013); Van Eykeren and Chu (2014); Deghat et al. (2016).

The two primary classes of critical aircraft faults are sensor faults (see Kobayashi and Simon, 2007; Alwi and Edwards, 2008; Berdjag et al., 2012; Van Eykeren and Chu, 2014; Hansen and Blanke, 2014; Deghat et al., 2016) and actuator failures (see De Persis et al., 2001; Shen et al., 2013). In this work, we consider sensor anomalies. Here, the term *anomaly* may refer to fault, bias, or attack. Sensor anomalies lead to erroneous state estimation and ultimately to incorrect controller operation (whether the controller be human-in-the-loop or autonomous (Kwon et al., 2014; Hansen and Blanke, 2014)). Efficient sensor anomaly detection methods aim to mitigate the negative impact of errors on the flight controller. One of the major difficulties in this field is model and sensor nonlinearity (Hansen and Blanke, 2014). In this work, we focus on a generic delta-wing aircraft, whose dynamics are nonlinear in the roll and roll-rate. Delta-wing aircraft and their variations have found application in high-speed, high-altitude, fighter-jet interceptors (Gordiner, 1995). Such aircraft are also common in current fixed wing UAV designs as they are relatively cheap to build, they can efficiently maximize wing surface area, and they are structurally robust.

Contribution: A fault-detection algorithm for a nonlinear dynamical aircraft model is proposed which is based on particle filtering (see Doucet et al., 2001; Ristic et al., 2004) and maximum likelihood methods. An advantage of the particle filtering method (over, e.g, unscented filter and extended Kalman filter) is that it can tackle highly nonlinear systems with non-Gaussian noise statistics. This filter is asymptotically optimal in the Bayesian sense and it can be rigorously proven that the approximation error is mostly uniformly bounded in time (i.e the approximation error does not accumulate over time) and is controlled in a clear fashion by the number of particles employed in the approximation (see Del Moral, 2004). As noted, here we consider a generic model for the roll dynamics of a delta-wing aircraft. Such aircraft are particularly susceptible to faulty sensor readings (and consequently) faulty actuation since they are inherently (open-loop) unstable (see Konstadinopoulos et al., 1985; Ahmadian et al., 2015). Despite this instability however, such aircraft are increasingly of interest as previously noted and thus effective fault-detection is well motivated here.

2. SYSTEM MODEL

2.1 Aircraft model

Consider a delta-wing aircraft, shown in Fig. 1, whose roll angle and roll rate can be controlled by ailerons which are

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the movable surfaces of the aircraft wing segments located symmetrically on the outboard portions. Moving one of the ailerons down and the other one up induces a positive or negative roll rate of the aircraft. The difference between the left and the right aileron positions is called the *differential aileron* which is denoted by $\delta_a(t)$ and is the control input signal for regulating the aircraft roll dynamics.

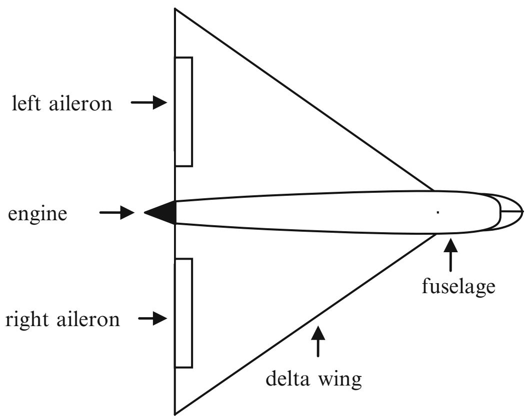

Fig. 1. Delta-wing aircraft. Source: Lavretsky and Wise (2012).

A generic delta wing rock dynamic model can be written as (Lavretsky and Wise, 2012, Chapter 9):

$$\ddot{\varphi} = \theta_1\varphi + \theta_2\dot{\varphi} + (\theta_3|\varphi| + \theta_4|\dot{\varphi}|)\dot{\varphi} + \theta_5\varphi^3 + \theta_6\delta_a + \nu, \quad (1)$$

where $\varphi(t)$ is the aircraft roll angle (deg), $\nu(t)$ is the system uncertainty/noise, and the constant parameters of the aircraft are (for example) specified by,

$$\begin{aligned} &\theta_1 = -0.018, \quad \theta_2 = 0.015, \quad \theta_3 = -0.062,\\ &\theta_4 = 0.009, \quad \theta_5 = 0.021, \quad \theta_6 = 0.75. \end{aligned}$$

Define $p(t) := \dot{\varphi}(t)$ as the roll rate (deg/s), and assume the control input signal $\delta_a(t)$ is a function of the measurements $y_1(t)$ and $y_2(t)$ which are, respectively, the possibly faulty measurements of $\varphi(t)$ and $p(t)$. Then the dynamic model (1) can be rewritten as

$$\begin{aligned} \underbrace{\begin{bmatrix}\dot{\varphi}\\ \dot{p}\end{bmatrix}}_{\dot{X}} &= \underbrace{\begin{bmatrix}0 & 1\\ \theta_1 & \theta_2\end{bmatrix}}_{A}\underbrace{\begin{bmatrix}\varphi\\ p\end{bmatrix}}_{X} + \underbrace{\begin{bmatrix}0\\ 1\end{bmatrix}}_{B}\Big(\theta_6\delta_a(y_1, y_2) + g(X) + \nu\Big) \\ \underbrace{\begin{bmatrix}y_1\\ y_2\end{bmatrix}}_{Y} &= \underbrace{\begin{bmatrix}\varphi\\ p\end{bmatrix}}_{X} + \underbrace{\alpha}_{\text{anomaly}} + \omega \end{aligned} \quad (2)$$

where

$$g(X) = \underbrace{[\theta_3 \;\; \theta_4 \;\; \theta_5]}_{\Theta^\top}\underbrace{\begin{bmatrix}|\varphi|p\\ |p|p\\ \varphi^3\end{bmatrix}}_{\Phi(\varphi,p)}, \quad (3)$$

$\alpha(t) \in \mathbb{R}^2$ denotes the sensor anomaly (excluding noise) and $\omega(t) \in \mathbb{R}^2$ denotes the measurement noise.

Summarising the above description of the aircraft motion model, we can write down the following general state-space description of the aircraft which will be used in the next section,

$$\begin{aligned} \dot{X} &= f(X, \nu)\\ Y &= h(X, \omega) = X + \alpha + \omega \end{aligned} \quad (4)$$

where f is a nonlinear function defined accordingly by the kinematic and dynamic equations previously stated. At this point we do not specify the noise statistics of ν and ω, but one may assume they are additive, zero-mean, Gaussian random variables with covariance matrices Q and R for convenience.

2.2 Control system

The control objective is to asymptotically track the state $X_{ref}(t)$ of the following reference model

$$\underbrace{\begin{bmatrix}\dot{\varphi}_{ref}\\ \dot{p}_{ref}\end{bmatrix}}_{\dot{X}_{ref}} = \underbrace{\begin{bmatrix}0 & 1\\ -\omega_n^2 & -2\zeta\omega_n\end{bmatrix}}_{A_{ref}}\underbrace{\begin{bmatrix}\varphi_{ref}\\ p_{ref}\end{bmatrix}}_{X_{ref}} + \underbrace{\begin{bmatrix}0\\ \omega_n^2\end{bmatrix}}_{B_{ref}}\underbrace{\varphi_{cmd}(t)}_{r(t)} \quad (5)$$

which can be driven by any bounded command $\varphi_{cmd}(t) = r(t)$, where ω_n and ζ are respectively the desired natural frequency and damping ratio.

In order to simplify the stability analysis and to focus attention on the anomaly detection method, we propose the following simple control law to control the roll angle and rate. More advanced control laws for the roll dynamic of a generic delta-wing aircraft can be found in the literature, see e.g. the adaptive controllers in Lavretsky and Wise (2012); Ahmadian et al. (2015). The control law is defined as

$$\delta_a(t) = K_x^\top\begin{bmatrix}y_1\\ y_2\end{bmatrix} + k_r r - \Theta^\top\Phi(y_1, y_2) \quad (6)$$

where Θ and Φ are defined in (3), $r(t) = \varphi_{cmd}(t)$ is the reference command, and $K_x \in \mathbb{R}^{2\times 1}$ and $k_r \in \mathbb{R}$ are constants which should be designed such that the system model in (2) is equal to the reference model (5) when the anomaly and uncertainty/noise terms are assumed to be zero.

To design the controller gains K_x and k_r, we equate the right hand sides of (2) and (5) and obtain that

$$K_x = -\frac{1}{\theta_6}\begin{bmatrix}\omega_n^2 + \theta_1\\ 2\zeta\omega_n + \theta_2\end{bmatrix}, \quad k_r = \frac{\omega_n^2}{\theta_6}. \quad (7)$$

Assume, for example, that the desired natural frequency and damping ratio of the system are $\omega_n = 1$ and $\zeta = 0.7$. Then

$$K_x = -\begin{bmatrix}1.31\\ 1.89\end{bmatrix}, \quad k_r = 1.33. \quad (8)$$

It is clear that when there is no fault and no noise in the system, the above control law stabilises the roll dynamic. We simulate the above controller to show the transient and steady state performance of the closed-loop system. The roll angle $\varphi(t)$ and roll rate $p(t)$ are depicted in Fig. 2 and Fig. 3, respectively. It can be seen that $\varphi(t)$ and $p(t)$ converge quickly to $\varphi_{ref}(t)$ and $p_{ref}(t)$.

3. BAYES FILTER

We now introduce the general Bayes filter and its approximation given by the so-called particle filter (or sequential Monte Carlo method). For more details see, e.g., Doucet et al. (2001);