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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^{*} Sensor Anomaly Detection and Recovery in the Roll D_{rel} of D_{rel} N_{rel} and N_{rel} via N_{rel} and N_{rel} N_{rel} Sensor Anomaly Detection and Recovery in the Roll
Dynamics of a Delta-Wing Aircraft via Monte Carlo Mohammad Deghat ∗ Evangelia Lampiri ∗∗ Mohammad Deghat ∗ Evangelia Lampiri ∗∗ Sensor Anomaly Detection and Recovery in the Roll ics of a Deita-Wing Aircraft via Mont
and Maximum Likelihood Methods * Mohammad Deghat ∗ Evangelia Lampiri ∗∗

Mohammad Deghat ∗ Evangelia Lampiri ∗∗ [∗] *CSIRO's Data61, Canberra Lab, Australia.* [∗] *CSIRO's Data61, Canberra Lab, Australia. nologies. University of Technology Sydney* (U ∗∗ *CSIRO's Data61, Sydney Lab, Australia, and the Centre for Health* ^{**} CSIRO's Databl, Sydney Lab, Australia, and the Centre for Health *Comparison Charlot Carro Technology Sydney (UTS),* Technologies, University of Technology Sydney (UTS), ESINO's Dataor, Syaney Lab, Australia, and the Centre for Health
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Abstract: This paper studies the problem of sensor anomaly detection, estimation and recovery for the 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. performance of the proposed algorithm. roll dynamic model of a generic delta-wing aircraft. The proposed algorithm employs particle filtering performance of the proposed algorithm. performance of the proposed algorithm.

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1. INTRODUCTION 1. INTRODUCTION F_{H} munoposition

ratif detection and recovery teeninques are attractive argoalgorithms in critical infrastructure, and such methods have algorithms in critical imagination, and such memods have
attracted considerable research interest; see e.g. the survey paatuacted considerable research interest, see e.g. the survey pa-
pers Isermann (1984); Hwang et al. (2010); Samy et al. (2011); Chen and Patton (2012). Observer-based fault detection techench and T attor (2012). Observer-based Tauft detection techniques are among the most common approaches used for fault niques 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 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. Fault detection and recovery techniques are attractive algoparticular modelling and uncertainty/noise assumptions.

Early detection of faults, anomalous behaviour and/or attacks Early detection of faints, anomalous behaviour and/or attacks and therefore fault detection and fault-tolerant control methods and therefore rath detection and rath-tolerant control memods
applied to aircraft flight control have received considerable
attention. The literature on fault-tolerant control and faultapplied to ancial light control have received considerable
attention. The literature on fault-tolerant control and faultdetection covers manned aircraft (see Brière and Traverse, 1993; Edwards et al., 2010), autonomous fixed wing UAVs (see 1999, Edwards et al., 2010), adionomous fixed wing OAVs (see 2014) 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 literature here is too broad to cover adequately; see the short
bibliography and the references therein: Patton (1991); Saif of the property and the references therein. Fatton (1991), San
and Guan (1993); Brière and Traverse (1993); De Persis et al. and Guan (1995), Briefe and Traverse (1995), De Fersis et al. (2001); Marcos et al. (2005); Kobayashi and Simon (2007); (2001) , Marcos et al. (2005) , Robayashi and Silhon (2007) ,
Alwi and Edwards (2008) ; Edwards et al. (2010) ; Alcorta-Aiwr and Edwards (2006), Edwards et al. (2010), Alcorda-
Garcia et al. (2011); Shen et al. (2013); Van Eykeren and Chu (2014) ; Deghat et al. (2016) . (2014) ; Deghat et al. (2016) .

The two primary classes of critical aircraft faults are sensor File two primary classes of critical ancient faults are sensor
faults (see Kobayashi and Simon, 2007; Alwi and Edwards,
2008: Berdiag et al., 2012: Van Eykeren and Chu, 2014: Hansen 2008; Berdjag et al., 2012; Van Eykeren and Chu, 2014; Hansen 2006, Bergag et al., 2012, Van Eykeren and Chu, 2014, Hansen
and Blanke, 2014; Deghat et al., 2016) and actuator failures 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 (see De Fersis et al., 2001, Shell 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 to fault, bias, or attack. Sensor anomalies lead to erroneous The two primary classes of critical aircraft faults are sensor
faults (see Kobayashi and Simon, 2007; Alwi and Edwards,
2008; Berdies et al., 2012; Ver Euleren and Chu, 2014; Unesen (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 anomary detection methods and to image the negative impact
of errors on the flight controller. One of the major difficulties of errors of the hight controller. One of the high difficulties
in this field is model and sensor nonlinearity (Hansen and Blanke, 2014). In this work, we focus on a generic deltabrank, 2014). In this work, we focus on a generic dena-
wing aircraft, whose dynamics are nonlinear in the roll and wing aircraft, whose dynamics are nonlinear in the roll and
roll-rate. Delta-wing aircraft and their variations have found ion-rate. Detta-wing ancraft and their variations have found
application in high-speed, high-altitude, fighter-jet interceptors application in lign-speed, ingin-articular, ligner-jet interceptors
(Gordiner, 1995). Such aircraft are also common in current (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 fixed wing OAV designs as they are relatively encap to build, they can efficiently maximize wing surface area, and they are structurally robust. state estimation and ultimately to incorrect controller operation α factority for a factor.

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 maxintering (see Doucet et al., 2001, Kisto et al., 2004) and max-
imum likelihood methods. An advantage of the particle filterinium intermood methods. An advantage of the particle inter-
ing method (over, e.g, unscented filter and extended Kalman ing inemot (over, e.g. unscended inter and extended Kannah Gaussian noise statistics. This filter is asymptotically optimal in the Bayesian sense and it can be rigorously proven that the 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 approximation error is mostry unforming bounded in three (i.e.
the approximation error does not accumulate over time) and is and 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 deta-wing ancian. Such ancian are particularly susceptible to
faulty sensor readings (and consequently) faulty actuation since
they are inherently (open-loop) unstable (see Konstadinopoulos they are inherently (open-loop) unstable (see Konstadinopoulos et al., 1985; Ahmadian et al., 2015). Despite this instability 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. noted and thus effective fault-detection is well motivated here. controlled in a clear fashion by the number of particles em-
cleared in the controlling (see Del Mars), 2004). As useful here we consider a generic model for the roll dynamics of a
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2. SYSTEM MODEL 2. SYSTEM MODEL

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

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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):

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

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,

$$
\theta_1 = -0.018, \quad \theta_2 = 0.015, \quad \theta_3 = -0.062, \n\theta_4 = 0.009, \quad \theta_5 = 0.021, \quad \theta_6 = 0.75.
$$

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

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

where

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

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

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

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

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

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

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

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

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);

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