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A Control Effectiveness Estimator with a Moving Horizon Robustness Modification for Fault-Tolerant Hexacopter Control

Philipp Niermeyer *,[1] **Mikhail Pak** * **Boris Lohmann** *

* *Department of Mechanical Engineering, Technical University of Munich, Institute of Automatic Control, Boltzmannstraße 15, 85748 Garching, Mail: philipp.niermeyer@tum.de*

Abstract: Online estimation of control effectiveness in combination with appropriate controller reconfiguration is a promising method for introducing a certain fault-tolerance into a control system. The contribution of this paper is twofold. First, it investigates the observability of the parameters to be determined for a hexacopter; second, a novel approach is introduced which combines moving horizon estimator (MHE) and Lyapunov-based methods. Conventional and proposed estimators are tuned and validated to assess their performance. Ease of implementation along with beneficial error characteristics are the main strength of the presented nonlinear MHE-augmented Lyapunov-based estimator.

Keywords: Fault Detection, Diagnosis, Identification, Isolation and Tolerance for Autonomous Vehicles; Autonomous Mobile Robots; Health monitoring and diagnosis

1. INTRODUCTION

The range of applications for small unmanned aircrafts is expanding rapidly as increasingly tailored configurations, e.g. Vertical Take Off and Landing (VTOL) capable airplanes, emerge. Still, multirotors range among the most popular Micro Aerial Vehicle (MAV) configurations due to their mechanical simplicity and ability to hover. If equipped with six and more rotors, their degree of redundancy w.r.t. actuator failures can be gradually increased, provided the failures are reliably identified and the controller is reconfigured accordingly (Achtelik et al. (2012)).

Two main approaches towards automatic recovery from partial or full actuator loss can be identified. First, Blanke et al. (2016) propose a structure based on fault detection, isolation and controller reconfiguration, experimentally verified in a hexacopter setting using dedicated linear observers for each fault scenario by Vey and Lunze (2016). Similarly, Saied et al. (2015) show experimental results for an octocopter using a single sliding-mode observer to identify the fault.

The above approaches have in common that they assume discrete failure scenarios. In contrast, the second approach employs real-valued parameters which capture actuator effectiveness. Thus, the problem can be cast as a nonlinear state or parameter estimation problem and tackled with methods from adaptive control. Dydek et al. (2013) presents and compares Model Reference Adaptive Control (MRAC) variants to compensate for partial actuator loss and more general model uncertainties. In Amoozgar et al. (2012), a Two-Stage Kalman filter for estimating the individual rotors' effectiveness is flight-tested under partial degradation on a quadrotor. Falconí et al. (2016) propose an architecture which identifies control effectiveness and simultaneously adapts the allocation of desired torques and thrust to the motor commands. Their approach is independent of attitude and position control, flight-tested and able to compensate for full and partial actuator loss.

This work ties to the conceptual ideas in the latter publications and focuses solely on the estimation of the control effectiveness. To our perception, too little effort has been taken to systematically review issues in the observer design process, comparison of existing and construction of alternative approaches to online control effectiveness estimation. Therefore, we chose to analyze observability and sensitivity of measurements to degradation of the motors and introduce a novel moving horizon modification to a conventional Lyapunov-function inspired approach to control effectiveness estimation. Finally, we compare its performance to a conventional Lyapunov-based estimator as well as a standard Moving Horizon Estimation (MHE) approach.

2. HEXACOPTER SYSTEM DYNAMICS

2.1 Notation, variables and dynamics

The operator $\mathrm{diag}(v)$ returns a matrix with the elements of vector v on its main diagonal. The skew symmetric operator $\langle\!\langle\cdot\rangle\!\rangle$ maps a vector x to a skew symmetric matrix such that $x \times y = \langle\!\langle x\rangle\!\rangle y$. We use operators $\mathrm{vertcat}(v, w) = \begin{bmatrix} v^{\mathrm{T}} & w^{\mathrm{T}}\end{bmatrix}^{\mathrm{T}}$ and $\mathrm{horzcat}(v, w) = [v \; w]$. Furthermore, $P \succ 0$ indicates that matrix P is positive definite. The airframe inertia tensor is given by $\mathcal{J} \in \mathbb{R}^{3\times3}$, $\omega \in \mathbb{R}^3$ denotes the rotational rate of the body-fixed frame w.r.t. the inertial frame with its components represented in body-

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fixed frame. Motor commands are denoted $u \in \mathbb{R}^6$, the corresponding effectiveness vector is $\lambda \in \mathbb{R}^6$.

We consider the noise perturbed dynamics of the rigid-body rotational dynamics

$$\dot{\omega} = \mathcal{J}^{-1}\left(\tau - \langle\!\langle\omega\rangle\!\rangle\mathcal{J}\omega + \nu_\omega^x\right); \tag{1a}$$

$$\dot{\lambda} = 0 + \nu_\lambda^x, \tag{1b}$$

where

$$\tau = B_\tau \operatorname{diag}(u)\lambda \in \mathbb{R}^3. \tag{2}$$

Both ω and λ are excited by process noise $\nu_\omega^x \in \mathbb{R}^3$ and $\nu_\lambda^x \in \mathbb{R}^6$ respectively, where ν_ω^x is modeled as a torque disturbance.

The measurement vector is given by

$$y = \operatorname{vertcat}(\omega, f_z) + \nu^y \in \mathbb{R}^4, \tag{3}$$

where $f_z = -m^{-1}B_T \operatorname{diag}(u)\lambda$ and $\nu^y = \operatorname{vertcat}(\nu_\omega^y, \nu_{f_z}^y)$ is measurement noise. Matrices $B_\tau \in \mathbb{R}^{3\times6}$ and $B_T \in \mathbb{R}^{1\times6}$ map the motor commands u to torques and thrust by combining airframe geometry and nominal propeller coefficients. Where favorable, we substitute $B = \operatorname{vertcat}(B_\tau, B_T)$. As gyro measurements are considered good in a sense that bias, drift and noise are not much of an issue on the considered time scale, we are particularly interested in estimating the control effectiveness λ. Note that elements of λ which exceed a value of one occur when nominal propeller coefficients are lower than the true coefficients, whereas values below one would indicate smaller coefficients than nominal. A complete failure corresponds to zero effectiveness.

2.2 Observability

From system and measurement equations, it is obvious that variation of λ within $\ker(B\operatorname{diag}(u))$ at each point in time will influence neither measurement nor state derivative. Thus, the question arises whether kernel variations in realistic flight scenarios are sufficiently large to effect available measurements. We therefore investigate local observability of the dynamics based on data from a simulated flight scenario at speeds of around 4 m/s, traversing a three-dimensional eight-type path while pointing the body-fixed x-axis towards a fixed point in inertial frame. We substitute $x = \operatorname{vertcat}(\omega, \lambda)$ and denote $f(x,u)$ the RHS of the differential equations (1) and $h(x,u)$ as the output map of (3). The system is said to be locally observable if, in the whole domain of definition,

$$Q_{\text{obs}}(x, \overset{[n-1]}{u}) = \operatorname{vertcat}(L_f^0, \ldots, L_f^{n-1})\frac{\partial h}{\partial x} \tag{4}$$

satisfies $\operatorname{rank}(Q_{\text{obs}}) = n$ where n is the state dimension (Birk and Zeitz (1992)) and L_f^k is the k-th Lie derivative w.r.t. the vector field f. Here, vector $\overset{[n-1]}{u} = \operatorname{vertcat}(u, \dot{u}, \ldots, \overset{(n-1)}{u})$ identifies the input and its derivatives. Figure 1 gives the singular values of Q_{obs} normalized to the largest singular value. While Q_{obs} has full rank at each time instant of the recorded data, we identify two particularly small singular values.

2.3 Sensitivity analysis

To gain additional insight, we solve the sensitivity ODE of Eq. (1a) w.r.t. λ, i.e.

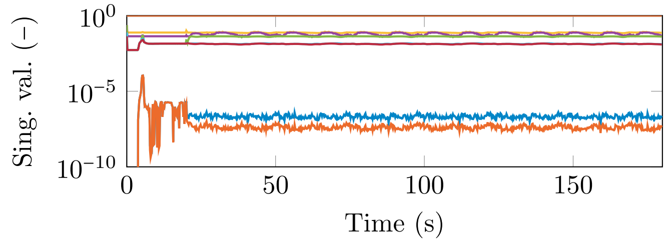

Figure 1. Normalized singular values of Q_{obs} over time

$$\dot{S}_\lambda(t) = \frac{\partial\dot{\omega}}{\partial\omega}(t)S_\lambda(t) + \frac{\partial\dot{\omega}}{\partial\lambda}(t) \tag{5}$$

in order to obtain $S(t) = \frac{\partial y}{\partial\lambda}(t)$ and with it by Eq. (3) the sensitivities of the measurement to parameter changes. Figure 2 gives the time history of $\frac{\partial y}{\partial\lambda}(t)$ transformed to an orthogonal basis of $\mathbb{R}^6$ whose first two basis vectors span the kernel of B. It can be seen that measurement sensitivity in off-kernel directions is by orders of magnitudes larger than in the kernel directions, just as expected.

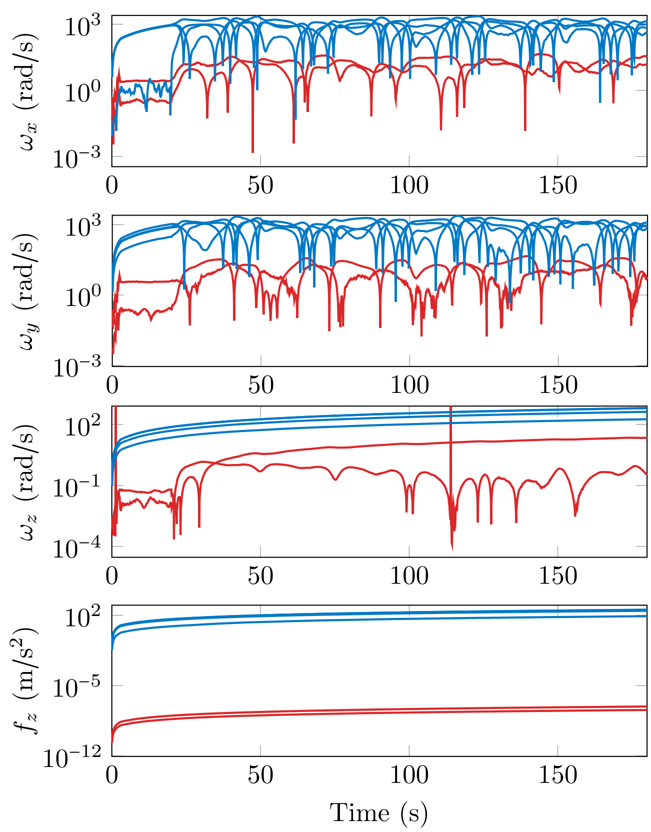

Figure 2. Sensitivity of measurements (absolute value) w.r.t. control effectiveness λ; red: kernel directions, blue: off-kernel directions

3. ESTIMATOR DESIGN

By extending the system dynamics (1) by a correction term σ, we obtain the observer dynamics

$$\dot{\hat{\omega}} = \mathcal{J}^{-1}\left(B_\tau \operatorname{diag}(u)\hat{\lambda} - \langle\!\langle\hat{\omega}\rangle\!\rangle\mathcal{J}\hat{\omega} + \sigma\right). \tag{6}$$

We write $\tilde{(\cdot)} = \hat{(\cdot)} - (\cdot)$ to denote the difference between estimated and true value, which gives the error dynamics