A Robust Observer with Gyroscopic Bias Correction for Rotational Dynamics

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Introduction

Motivation

- Attitude estimation for aerospace applications
- Often derived using attitude kinematics [1]
- Design estimator targeted for UAV estimation
- Joint estimation of gyroscopic rates and biases

Contributions

- Result for attitude *dynamics* (using torques)
- Observer with uniform stability properties
- Produces filtered attitude rates for control

Takeaway

- Extension of result in [1] to include torques and known inertia for UAV applications
- Proof of uniform LES (ULES) and uniform almost GAS (UaGAS) by Matrosov theory [2]



^{[1] -} Mahony, Hamel, and Pflimlin, "Nonlinear complementary filters on the special orthogonal group" 2008

^{[2] -} Loría, Panteley, Popovic, et al., "A nested Matrosov theorem and persistency of excitation for uniform convergence in stable nonautonomous systems" 2005: 🕨 🚊

Introduction

Presentation outline

- Setting and definitions
- Observer design
 - Step 1: Angular momentum estimator
 - Step 2: Gyroscopic bias estimator
 - Step 3: Convex combination of estimators

- Step 4: Implementation aspects
- Simulations
 - Qualitative example
 - Quantitative comparison
 - Tuning the observer
- Conclusions

Setting and Definitions

• The motion of a rotating rigid body configured on $R \in SO(3)$ is governed by the dynamics

$$\dot{R} = RS(\omega)$$
 (1a)

$$J\dot{\omega} = S(J\omega)\omega + \tau,$$
 (1b)

where $J = J^{\top} > 0$ is the inertia matrix and $\tau \in R^3$ is the total moment vector in the body frame. • Measured outputs

$$y_0 = \omega + b$$
 $y_i = R^{\top} v_i$ $i = 1, \dots, n,$ (2)

where b is an unknown constant, and v_i denote n known inertial directions (n=2, but wlog n = 3).

Problem

Consider the outputs (2). Design an observer/filter which produces estimates \hat{R} , $\hat{\omega}$, and \hat{b} such that the point (1,0,0) of the estimation error dynamics ($\tilde{R}, \tilde{\omega}, \tilde{b}$), given by

 $\tilde{R} = \hat{R}R^{\top}$ $\tilde{\omega} = \hat{\omega} - \omega$ $\tilde{b} = \hat{b} - b,$ (3)

is almost globally and locally exponentially stable.

Angular momentum estimator

• Estimation errors

$$\tilde{R} = \hat{R}R^{\top} \qquad \qquad \tilde{\ell} = \hat{\ell} - RJ\omega \qquad (4)$$

• Observer update

$$\dot{\hat{R}} = \hat{R}S\left(J^{-1}R^{\top}\hat{\ell} - k_R\tilde{r}_k\right) \qquad \qquad \dot{\hat{\ell}} = R\tau - k_\ell R J^{-1}\tilde{r}_k \tag{5a}$$

where $k_R > 0$, $k_\ell > 0$, and

$$\tilde{r}_{k} = \sum_{i=1}^{n} k_{i} S(\hat{R}^{\top} v_{i}) R^{\top} v_{i} = \sum_{i=1}^{n} k_{i} S(\hat{R}^{\top} v_{i}) y_{i}.$$
(5b)

Proposition (1)

Consider the observer (5) in closed-loop with the attitude dynamics. If the weights k_i are chosen such that $\sum_{i=1}^{n} k_i v_i v_i^{\top}$ has distinct eigenvalues λ_i , i.e., $\lambda_3 > \lambda_2 > \lambda_1 > 0$, then the estimation errors (4) are UaGAS and ULES towards (1,0).

Gyroscopic bias estimator [1]

Estimation errors

$$\tilde{b} = \hat{b} - b$$
 $\tilde{R} = \hat{R}R^{\top}$ (6)

Observer update

$$\dot{\hat{b}} = k_b \tilde{r}_k \qquad \qquad \dot{\hat{R}} = \hat{R}S(y_0 - \hat{b} - k_R \tilde{r}_k) \tag{7}$$

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with $k_b > 0$, $k_R > 0$, $J = J^{\top} > 0$ and \tilde{r}_k as in (5b) previously.

Proposition (2)

Consider the observer (7) in closed-loop with the kinematics. If ω and $\dot{\omega}$ are bounded and the weights k_i are chosen such that $\sum_{i=1}^{n} k_i v_i v_i^{\top}$ has distinct eigenvalues λ_i , i.e., $\lambda_3 > \lambda_2 > \lambda_1 > 0$, then the estimation errors (6) are UaGAS and ULES towards (1,0).

^{[1] -} Mahony, Hamel, and Pflimlin, "Nonlinear complementary filters on the special orthogonal group" 2008

Convex combination of the observers from Step #1 and Step #2 and some additional terms

• Estimation errors

$$\tilde{R} = \hat{R}R^{\top} \qquad \tilde{\ell} = \hat{\ell} - RJ\omega \qquad \tilde{b} = \hat{b} - b, \qquad (8)$$

• Observer update

$$\hat{\boldsymbol{b}} = \boldsymbol{k}_{\boldsymbol{b}} \tilde{\boldsymbol{r}}_{\boldsymbol{k}} - \alpha k_{\boldsymbol{b}} k_{\alpha} J R^{\top} [\hat{\ell} - R J (y_0 - \hat{b})]$$
(9a)

$$\dot{\hat{R}} = \hat{R}S\left(\alpha J^{-1}R^{\top}\hat{\ell} - (1-\alpha)(\mathbf{y}_0 - \hat{\mathbf{b}}) - k_R\tilde{\mathbf{r}}_k\right)$$
(9b)

$$\hat{\ell} = R\tau - k_{\ell}RJ^{-1}\tilde{r}_{k} - (1-\alpha)k_{\ell}k_{\alpha}[\hat{\ell} - RJ(y_{0} - \hat{b})]$$
(9c)

$$\hat{\omega} = J^{-1} \hat{R}^{\top} \hat{\ell}, \tag{9d}$$

with $k_b > 0$, $k_\alpha > 0$, $k_b > 0$, $k_R > 0$, $k_\ell > 0$, $0 < \alpha < 1$, and \tilde{r}_k as defined in (5b) previously.

Proposition (3)

Consider the observer (9) in closed-loop with the dynamics. If k_i are chosen such that $\sum_{i=1}^{n} k_i v_i v_i^{\top}$ has distinct eigenvalues λ_i , then the estimation errors are UaGAS and ULES towards (1,0,0).

Using the Lyapunov function from Step #1 and #2

Step #1:
$$V_{(\#1)} = k_{\ell} \sum_{i=1}^{n} \frac{k_{i}}{2} \left\| \tilde{R} \mathbf{v}_{i} - \mathbf{v}_{i} \right\|_{2}^{2} + \frac{1}{2} \tilde{\ell}^{\top} \tilde{\ell}$$
 (10a)

Step #2:
$$V_{(\#2)} = k_b \sum_{i=1}^n \frac{k_i}{2} \left\| \tilde{R} v_i - v_i \right\|_2^2 + \frac{1}{2} \tilde{b}^\top \tilde{b}$$
 (10b)

Step #3:
$$V_{(\#3)} = k_{\ell} k_{b} \sum_{i=1}^{n} \frac{k_{i}}{2} \left\| \tilde{R} v_{i} - v_{i} \right\|_{2}^{2} + \frac{k_{\ell}}{2} (1 - \alpha) \tilde{b}^{\top} \tilde{b} + \frac{k_{b}}{2} \alpha \tilde{\ell}^{\top} \tilde{\ell}$$
 (10c)

Differentiation along the error dynamics yields

$$\dot{V}_{(\#3)} = -k_{\ell}k_{b}k_{R} \|\tilde{r}_{k}\|_{2}^{2} - \alpha(1-\alpha)k_{\ell}k_{b}k_{\alpha}\|\tilde{\delta}_{L}\|_{2}^{2} \leq 0,$$
(11)

yielding boundedness of both $\dot{\tilde{r}}_k$ and $\ddot{\tilde{r}}_k$, and the proof is completed with a Matrosov result [2].

^{[2] -} Loría, Panteley, Popovic, et al., "A nested Matrosov theorem and persistency of excitation for uniform convergence in stable nonautonomous systems" 2005 🕨 💿 🕘 🗠 🔍

Properties

- Approaches the observers in step #1 and step #2 if $\alpha \to \{1,0\}$
- Potential to get the best of both (smooth rate estimates and bias estimates)
- All measurement noise passes through an integrator \Rightarrow impacts noise-error gain
- Uniform stability properties \Rightarrow robustness to bounded perturbations [3]

Implementation aspects

- Possible to get slow error decays (e.g., if $lpha o \{0,1\}$), needs to be tuned with care
- Not strictly implementable as written (*R* is not known)

But there is a remedy!

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^{[3] -} Khalil, Nonlinear Systems 2002

Making the estimator implementable

- In the estimate update (9) of Proposition 3, we require R which is not known
- Here, we can replace instances of R in the estimate update by

$$\bar{R} = \left(\sum_{i=1}^{n} k_i v_i v_i^{\top}\right)^{-1} \sum_{i=1}^{n} k_i v_i y_i^{\top}.$$
(12)

Proposition (4)

Consider the observer (9) in closed-loop with the dynamics. If the observer is defined as in Proposition 3 with R replaced by \overline{R} , then the estimation errors are UaGAS and ULES towards (1,0,0).

Remark

This is only used on the right-hand-side of the ODE, and thus this (potentially noisy) reconstruction of R is solely used to define the innovations of the observer, and filtered through the integrators.

Simulations - Qualitative

Qualitative simulation result

- Observer in Proposition 4
- Discrete-time implementation (500Hz)
- This is an ideal setting, no noise
- Dense inertia matrix
- Large initial estimation errors

Takeaway

- Proof of UaGAS/ULES, but initial transients decay with rates similar to the local errors
- The transient system response depends on the observer tuning, can be made slow if α ∈ (0, 1) is close to end-points



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Simulations - Quantitative

- Parameters: $\theta = \{R_0, \omega_0, b, \hat{R}_0, \hat{\omega}_0, \hat{b}_0\}$ sampled uniformly for each MC run
- Movement: significant, driven by $au(t) = (\sin(t+1), \sin(2t+2), \sin(3t+3))^{ op} \in \mathbb{R}^3$
- Noise: sampled at 500 Hz with $\delta_i \sim \mathcal{N}(0, 0.1^2 I)$, where

$$\begin{split} y_0(hk) &= \omega(hk) + b(hk) + \delta_0(hk) \\ \bar{y}_i(hk) &= R(hk)^\top v_i + \delta_i(hk) \\ y_i(hk) &= \bar{y}_i(hk) / \|\bar{y}_i(hk)\|_2 \end{split} \qquad i = 1, \dots, 3, \end{split}$$

• Measure: Average L2-norms over different time intervals

$$\text{RMSE}_{\mathcal{L}_{2}([a,b])}(x) = \Big(\frac{1}{N_{MC}}\sum_{i=1}^{N_{MC}}\int_{a}^{b} \|x^{(i)}(t)\|_{2}^{2} \mathrm{d}t\Big)^{1/2}.$$

• Signals: attitude error $\Psi(\tilde{R}) = \frac{1}{2} \text{Tr}(I - \tilde{R})$, attitude rate error $\tilde{\omega}$ and bias error \tilde{b}

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| Measure $\operatorname{RMSE}_{\mathcal{L}_2([0,T])}(x)$ $\operatorname{RMSE}_{\mathcal{L}_2([T-1,T])}(x)$ | | | | | | | | | |
|---|---------------------|------------------|--------|-----------------------|------------------|-------------|--|--|--|
| Signal | $ \Psi(\tilde{R}) $ | $\tilde{\omega}$ | β μ | $\Psi(ilde{R})$ | $\tilde{\omega}$ | \tilde{b} | | | |
| Prop. 1 | 0.560 | 2.571 | 2.629 | $3.043 \cdot 10^{-5}$ | 0.022 | 0.178 | | | |
| Prop. 2 | 0.577 | 2.463 | 2.401 | $2.718 \cdot 10^{-5}$ | 0.177 | 0.016 | | | |
| Prop. 4 | 0.570 | 2.389 | 2.226 | $2.809 \cdot 10^{-5}$ | 0.021 | 0.016 | | | |

Table: RMSEs of transient and stationary errors categorized by signals and observers.

Simulations - Quantitative

- Parameters: $\theta = \{R_0, \omega_0, b, \hat{R}_0, \hat{\omega}_0, \hat{b}_0\}$ sampled uniformly for each MC run
- Movement: significant, driven by $au(t) = (\sin(t+1), \sin(2t+2), \sin(3t+3))^{ op} \in \mathbb{R}^3$
- Noise: sampled at 500 Hz with $\delta_i \sim \mathcal{N}(0, 0.1^2 I)$
- Measure: Average \mathcal{L}_2 -norms over different time intervals

| Measure RMSE _{$\mathcal{L}_2([0,T])$} (x) | | | | $\mathrm{RMSE}_{\mathcal{L}_2([T-1,T])}(x)$ | | |
|---|------------------|------------------|-----------------|---|------------------|------------|
| Signal | $\Psi(ilde{R})$ | $\tilde{\omega}$ | $ $ \tilde{b} | $\Psi(ilde{R})$ | $\tilde{\omega}$ | $	ilde{b}$ |
| Prop. 1 | 0.560 | 2.571 | 2.629 | $3.043 \cdot 10^{-5}$ | 0.022 | 0.178 |
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Table: RMSEs of transient and stationary errors categorized by signals and observers.

Takeaway

Relatively small differences in the transients, but significant differences in the stationary errors $\tilde{\omega}$ and \tilde{b} . The observer in Proposition 4 is less impacted by noise in these errors.

Simulations - Tuning

Observer tuning

• Express local perturbation about identity error

$$\tilde{R} \approx I + S(\tilde{\epsilon})$$
 (13)

• Consider noise $\delta_i \in \mathbb{R}^3$ on the measurements, as

$$y_0 = w + b + \delta_0, \qquad y_i = R^{\top} (I + S(\delta_i)) v_i.$$
 (14)

• Under a stationary rotation R, we get a linear system

$$\dot{\tilde{x}} = A\tilde{x} + B\delta. \tag{15}$$

from measurement noises $\delta^{\top} = (\delta_0^{\top}, \delta_1^{\top}, \delta_2^{\top}, \delta_3^{\top}) \in \mathbb{R}^{12}$ to the local estimation errors $\tilde{x}^{\top} = (\tilde{\epsilon}^{\top}, \tilde{\omega}^{\top}, \tilde{b}^{\top}) \in \mathbb{R}^{9}$.

Takeaway

Tune based on the spectrum of A, and the properties of the system $G(s) = (sI - A)^{-1}B$. For example, we get a balanced spectrum and good attenuation of the measurement noise with $\alpha \approx 0.3$ when fixing the other controller parameters.



Conclusions

Summary

- Observer for angular momentum (step #1)
- Combined with result by Mahony [1] (step #3)
- Addressing implementation aspects (step #4)
- Robust attitude observer, demonstrated both in theory and simulations
- Code for discrete-time implementation with quaternions and RK4
- Additional mathematical details in extended arXiv paper [4]

Main insights

- We can take a "convex combination" of observers
- Proofs come with uniform stability properties

^{[1] -} Mahony, Hamel, and Pflimlin, "Nonlinear complementary filters on the special orthogonal group" 2008

^{[4] -} Lefeber, Greiff, and Robertsson, "A Robust Observer with Gyroscopic Bias Correction for Rotational Dynamics" 2023

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