Application: Pose Estimation

Workshop 10 - Geometric Observers on Manifolds and Lie-Groups

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Motivation

What is common to these vehicles?



Motivation

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Motivation Dynamical Model

• The configuration of any vehicle (rigid body) can be represented by a rotation matrix $R \in SO(3)$ and a position vector $p \in \mathbb{R}^3$ such that

$$\begin{cases} \dot{R} &= R\omega_{\times}, \\ \dot{p} &= RV, \end{cases}$$

where ω and V are respectively the angular and linear velocities expressed in body-frame.



• The motion of a rigid body in an ideal fluid satisfies the Euler-Lagrange equations

$$\begin{cases} \mathbf{J}\dot{\omega} &= \mathbf{J}\omega_{\times}\omega + \mathbf{M}V_{\times}V + f_{\omega}\\ \mathbf{M}\dot{V} &= \mathbf{M}V_{\times}\omega + f_{V}, \end{cases}$$

where $[f_{\omega}, f_V]$ is the resultant generalized force acting on the main body.



 $^{{\}bf J}$ and ${\bf M}$ respectively represent the inertia matrix and the added mass matrix.

Outline

Introduction & Motivation

2 Models and Sensors

- Inertial Measurement Unit (IMU)
- Inertial-Frame Position Information
- Body-Frame Position Information

Inertial Navigation Systems

- Inertial Odometry & GPS-Aided INS
- Universal Observers: Inertial-Frame Position Information
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 - Inertial-Frame Kinematics
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Conclusion

Inertial Measurement Unit (IMU)



gyroscope: $\omega^{y} = \omega$, (1) accelerometer: $a^{\mathcal{B}} = R^{\top}(\dot{v} - g)$, (2) magnetometer (Optional): $m^{\mathcal{B}} = R^{\top}m$, (3)

- m: a constant and know earth's magnetic field
- g: inertial-frame acceleration due to gravity
- v: inertial-frame linear velocity

remark

For simplicity, we will consider bias-free measurements in this talk.

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Application: Pose Estimation

Inertial Measurement Unit (IMU)

IMU Kinematics



Inputs are $(a^{\mathcal{B}}, \omega)$

Objective

Estimate the extended pose (p, v, R) using measurements y = h(p, R).

• The estimators proposed here evolve on $SO(3) \times \mathbb{R}^n$

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Inertial Measurement Unit (IMU) IMU Kinematics

From the dynamical model of the rigid-body:

$$\begin{cases} \dot{p} &= v, \\ \dot{v} &= g + R a^{\mathcal{B}}, \\ \dot{R} &= R \omega_{\times}, \end{cases} \implies \begin{cases} \dot{p}^{\mathcal{B}} &= -[\omega]_{\times} p^{\mathcal{B}} + v^{\mathcal{B}}, \\ \dot{v}^{\mathcal{B}} &= -[\omega]_{\times} v^{\mathcal{B}} + a^{\mathcal{B}} + g^{\mathcal{B}}, \\ \dot{R} &= R \omega_{\times}, \end{cases}$$

Coupling is through:

- a := Ra^B: unknown apparent acceleration, capturing all non-gravitational forces applied to the vehicle, expressed in {I}.
- $g^{\mathcal{B}} := R^{\top}g$: unknown body-frame gravitational forces.

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Full position (e.g., GPS)



y = p

Range measurements (e.g., Ultra-wideband (UWB))



 $d_i = \|p - p_i\|, \quad i = 1, \cdots, n.$

Range measurements (e.g., Ultra-wideband (UWB))

At least 4 non-coplanar source points are needed located at p_i .

$$d_i = \|p - p_i\|, \quad i = 1, \cdots, n.$$

Output equaion:

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$$y_i := \frac{1}{2} \left(d_i^2 - d_1^2 - \|p_i\|^2 + \|p_1\|^2 \right), \quad i = 2, \cdots, n.$$

$$y = \begin{bmatrix} (p_1 - p_2)^\top \\ \vdots \\ (p_1 - p_n)^\top \end{bmatrix} p := C_p p$$
(4)

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Assumption (Observability) $\operatorname{rank}(C_p) = 3.$

Application: Pose Estimation

Bearing measurements (e.g., motion capture system)



Bearing measurements (e.g., motion capture system)

$$b_i = R_i^{\top} \frac{p - p_i}{\|p - p_i\|}, \quad i = 1, \cdots, n,$$

R_i ∈ SO(3): Orientation of camera *i* w.r.t. the inertial frame. *p_i*: Position of camera *i* in the inertial frame.

Bearing measurements (e.g., motion capture system)

$$b_i = R_i^{\top} \frac{p - p_i}{\|p - p_i\|}, \quad i = 1, \cdots, n,$$

- $R_i \in SO(3)$: Orientation of camera *i* w.r.t. the inertial frame.
- p_i : Position of camera *i* in the inertial frame.
- Note that

$$\Pi(b_i)R_i^ op(p-p_i)=0$$

where $\Pi(z) := I - zz^{\top}$ is the orthogonal projection.

Bearing measurements (e.g., motion capture system)

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- $R_i \in SO(3)$: Orientation of camera *i* w.r.t. the inertial frame.
- p_i: Position of camera i in the inertial frame.
- Note that

$$\Pi(b_i)R_i^\top(p-p_i)=0$$

where $\Pi(z) := I - zz^{\top}$ is the orthogonal projection.

Therefore, we obtain the following output vector

$$y = \begin{bmatrix} \Pi(b_1)R_1^\top p_1 \\ \vdots \\ \Pi(b_n)R_n^\top p_n \end{bmatrix} = \begin{bmatrix} \Pi(b_1)R_1^\top \\ \vdots \\ \Pi(b_n)R_n^\top \end{bmatrix} p := C_p(t)p.$$

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Conclusion

Body-Frame Position Information

Vision: Stereo vs. Monocular



Figure 1: (a) monocular vision system (b) stereo vision system.

Body-Frame Position Information

Vision: Stereo vs. Monocular

Let p_i denote the (constant and known) position of the *i*-th landmark in frame $\{\mathcal{I}\}$, and

$$p_i^{\mathcal{B}} := R^{\top}(p_i - p)$$

denote the position of the *i*-th landmark in frame $\{B\}$

1) Stereo-bearing measurements:

$$y_{i}^{s} := \frac{p_{i}^{C_{s}}}{\|p_{i}^{C_{s}}\|} = \frac{R_{cs}^{\top}(p_{i}^{\mathcal{B}} - p_{cs})}{\|p_{i}^{\mathcal{B}} - p_{cs}\|}, \ i \in \{1, 2, \dots, N\}, s \in \{1, 2\}$$
(5)

where $p_i^{C_s} = R_{cs}^{\top}(p_i^{\mathcal{B}} - p_{cs}).$

2) Monocular-bearing measurements:

$$y_{i} := \frac{p_{i}^{\mathcal{C}}}{\|p_{i}^{\mathcal{C}}\|} = \frac{R_{c}^{\top}(p_{i}^{\mathcal{B}} - p_{c})}{\|p_{i}^{\mathcal{B}} - p_{c}\|}, \ i \in \{1, 2, \dots, N\}$$
(6)

where $p_i^{\mathcal{C}} = R_c^{\top}(p_i^{\mathcal{B}} - p_c).$

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Inertial Navigation Systems Inertial Odometry



- Determination of the attitude, position and linear velocity
- Relies on the knowledge of the initial conditions
- Sensitive to low frequency noise (drift caused by the integration)

Inertial Navigation Systems

GPS-Aided Inertial Navigation



• NOT reliable during aggressive dynamic maneuvers

T. H. Bryne, J. M. Hansen, R. H. Rogne, et al., "Nonlinear observers for integrated INS/GNSS navigation: Implementation aspects," *IEEE Control Systems Magazine*, vol. 37, no. 3, pp. 59–86, 2017.

S. Bonnabel, P. Martin, and P. Rouchon, "Symmetry-preserving observers," IEEE Transactions on Automatic Control, vol. 53, no. 11, pp. 2514–2526, 2008.

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Universal Observers: Inertial-Frame Position Information Translational Dynamics

Let $x := (p, v) \in \mathbb{R}^6$. The dynamics of x are written as:

$$\dot{x} = Ax + B(g + a),$$
 (7)
 $y = Cx,$ (8)

where the matrices A, B and C are defined as follows:

$$A = \begin{bmatrix} 0_{3\times3} & I_3 \\ 0_{3\times3} & 0_{3\times3} \end{bmatrix}, B := \begin{bmatrix} 0_{3\times3} \\ I_3 \end{bmatrix}, C = \begin{bmatrix} C_p^\top \\ 0_{3\times m} \end{bmatrix}^\top.$$
(9)

• Linear time-invariant system with unknown input a

• We only measure $a^{\mathcal{B}} = R^{\top}a$ (in body-frame)

Assumption

C is constant (e.g., UWB range or GPS position measurements)

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Application: Pose Estimation

Common estimation approach (ad-hoc method)

Assumption

Negligible acceleration, i.e., $a \approx -g$.



Common estimation approach (ad-hoc method)

Assumption

Negligible acceleration, i.e., $a \approx -g$.

Attitude observer
$$\begin{cases} \dot{\hat{R}} &= \hat{R}[\omega + \sigma_R]_{\times}, \\ \sigma_R &= \rho_1(m_B \times \hat{R}^\top m) + \rho_2(a^{\mathcal{B}} \times \hat{R}^\top(-g)). \end{cases}$$

Translational Observer
$$\begin{cases} \dot{\hat{x}} = A\hat{x} + B(g + \hat{R}a^{\mathcal{B}}) + K(y - C\hat{x}) \\ (A - KC) \text{ is Hurwitz} \end{cases}$$

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R. Mahony, T. Hamel and J. Pflimlin, "Nonlinear Complementary Filters on the Special Orthogonal Group," in IEEE TAC, 2008.

H. F. Grip et al. "Attitude Estimation Using Biased Gyro and Vector Measurements With Time-Varying Reference Vectors," in IEEE TAC, 2012.

Proposed nonlinear observer



- The proposed observer introduces coupling between the translational estimator and the rotational estimator through their innovation terms.
- This additional coupling is important to guarantee the stability of the observer without the "small" acceleration assumption.

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Application: Pose Estimation

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Universal Observers: Inertial-Frame Position Information Translational Motion Observer

Let
$$K = L_{\gamma}K_0$$
 with $L_{\gamma} = \text{blockdiag}(\gamma I_3, \gamma^2 I_3)$ and $\gamma \ge 1$:
 $\dot{\hat{x}} = A\hat{x} + B(g + \hat{R}a^B) + K(y - C\hat{x}) + \sigma_x$

where $(A - K_0 C)$ is Hurwitz and

$$\sigma_{\mathsf{X}} = -k_{\mathsf{R}}(\mathsf{A} - \mathsf{K}\mathsf{C})^{-1}B[\hat{\mathsf{R}}\sigma_{\mathsf{R}}]_{\mathsf{X}}\hat{\mathsf{R}}\mathsf{a}^{\mathcal{B}}$$

- The matrix L_γ is introduced to assign a certain time-scaling structure between the different estimation errors.
- The expression of σ_{χ} is obtained through Lyapunov analysis.

Universal Observers: Inertial-Frame Position Information Rotational Motion Observer

Consider the "nonlinear complementary filter"-type observer

$$\hat{\hat{R}} = \hat{R}[\omega + \sigma_R]_{ imes}$$

with

$$\sigma_R = \rho_1(m_B \times \hat{R}^\top m_I) + \rho_2(a^B \times \hat{R}^\top \operatorname{sat}(B^\top K(y - C\hat{x}))).$$

• sat: is a saturation function

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Application: Pose Estimation

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Universal Observers: Inertial-Frame Position Information Stability Result

Estimation errors:

$$\tilde{R} := R\hat{R}^{\top}, \quad \tilde{x} := x - \hat{x}.$$
(10)

• Coupled auxiliary error variable:

$$\zeta := L_{\gamma}^{-1} \left[(A - KC)\tilde{x} + B(I - \tilde{R})^{\top} a \right].$$
(11)

• Attitude innovation term σ_R :

$$\sigma_{R} = \rho_{1}(\hat{R}m^{\mathcal{B}} \times m) + \rho_{2}(\hat{R}a^{\mathcal{B}} \times a) - \rho_{2}\gamma(\hat{R}a^{\mathcal{B}} \times B^{\top}\zeta). \quad (12)$$

Closed-loop dynamics

$$\tilde{\tilde{R}} = -\tilde{R}[\sigma_R(\tilde{R},\zeta,t)]_{\times},\tag{13}$$

$$\frac{1}{\gamma}\dot{\zeta} = (A - PC^{\top}QC)\zeta + \frac{1}{\gamma^2}B(I - \tilde{R})^{\top}\dot{a}(t).$$
(14)

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Universal Observers: Inertial-Frame Position Information Stability Result

Assumption

- *m* and *a*(*t*) are not collinear for all times
- ω , a, a are uniformly bounded

Theorem (Almost semi-global exponential stability)

For all initial conditions (except attitude errors at 180°), there exist (high) gains such that the estimation error converges exponentially to zero.

- Although, sufficiently large gains are needed in the proof, simulation results demonstrate that this is very conservative.
- Without magnetometer, similar result is obtained if $Ra^{\mathcal{B}}$ is PE

Simulation Results: Range measurements



Simulation Results: Range measurements

• Circular trajectory (with increasing acceleration):

$$p(t) = \begin{bmatrix} \cos(2\pi t^2/100) \\ \sin(2\pi t^2/100) \\ 1 \end{bmatrix}.$$
 (15)

Angular velocity:

$$\omega(t) = \begin{bmatrix} \sin(0.2t) \\ \cos(0.1t) \\ \sin(0.3t + \pi/6) \end{bmatrix},$$
(16)

Anchors:

$$p_1 = [1 \ 1 \ 2]^\top, \tag{17}$$

$$p_2 = [1 \ 3 \ 0]^{\top}, \tag{18}$$

$$p_3 = [0 \ 1 \ 1]^\top, \tag{19}$$

$$p_4 = [6 \ 5 \ 5]^\top. \tag{20}$$

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Simulation Results: Range measurements

| Estimated trajectory |
|----------------------|
| True trajectory |
Simulation Results: Range measurements



Figure 2: As the acceleration increases, the adhoc estimator drifts away from the true trajectory while the proposed estimator is stable.

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|------------------|------------------------------|---------------|---------|
| | | | |

Simulation Results: Range measurements



Figure 3: Position estimation errors.

Extended Translational Dynamics

Let $x := (p, v, a) \in \mathbb{R}^9$.

$$\dot{x} = Ax + B_1g + B_2\dot{a}$$
$$y = C(t)x$$

$$A = \begin{bmatrix} 0 & I & 0 \\ 0 & 0 & I \\ 0 & 0 & 0 \end{bmatrix}, B_1 := \begin{bmatrix} 0 \\ I \\ 0 \end{bmatrix}, B_2 := \begin{bmatrix} 0 \\ 0 \\ I \end{bmatrix}, \quad C(t) = \begin{bmatrix} C_{\rho}(t) \\ 0 \\ 0 \end{bmatrix}^{\top}$$

• Linear system with unknown input \dot{a} (jerk)

• We only measure $a^{\mathcal{B}} = R^{\top}a$

Translational Motion Observer

Consider the nonlinear observer

$$\begin{cases} \hat{x} = \hat{z} + B_2 \hat{R} a^{\mathcal{B}} \\ \dot{\hat{z}} = A \hat{x} + B_1 g + \mathcal{K}(t) (y - \mathcal{C}(t) \hat{x}) - B_2 \hat{R}[\sigma_R]_{\times} a^{\mathcal{B}} \end{cases}$$

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Consider the nonlinear observer

$$\begin{cases} \hat{x} = \hat{z} + B_2 \hat{R} a^{\mathcal{B}} \\ \dot{\hat{z}} = A \hat{x} + B_1 g + K(t) (y - C(t) \hat{x}) - B_2 \hat{R} [\sigma_R]_{\times} a^{\mathcal{B}} \end{cases}$$

• If $\hat{R} \rightarrow R$, this is equivalent to the **Luenberger-type observer**

$$\dot{\hat{x}} = A\hat{x} + B_1g + B_2\dot{a} + K(t)(y - C(t)\hat{x}).$$

Translational Motion Observer

Consider the nonlinear observer

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• If $\hat{R} \rightarrow R$, this is equivalent to the Luenberger-type observer

$$\dot{\hat{x}}=A\hat{x}+B_1g+B_2\dot{a}+K(t)(y-C(t)\hat{x}).$$

• $K(t) = \gamma L_{\gamma} P(t) C(t)^{\top} Q(t)$, with $\gamma \ge 1$, $L_{\gamma} = \text{blockdiag}(I_3, \gamma I_3, \gamma^2 I_3)$ and P(t) is solution of the CRE

$$\frac{1}{\gamma}\dot{P} = AP + PA^{\top} - PC(t)^{\top}Q(t)C(t)P + V(t),$$

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Universal Observers: Inertial-Frame Position Information Rotational Motion Observer

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Universal Observers: Inertial-Frame Position Information Stability Result # 2

Assumption

- Pair $(A, C(\cdot))$ is uniformly observable
- m and a(t) are not collinear for all times
- ω , a, a are uniformly bounded

Theorem (Almost semi-global exponential stability)

For all initial conditions (except attitude errors at 180°), there exist (high) gains such that the estimation error converges exponentially to zero.

• Although, sufficiently large gains are needed in the proof, simulation results demonstrate that this is very conservative.

S. Berkane, A. Tayebi, and S. De Marco, "A nonlinear navigation observer using imu and generic position information," Automatica, vol. 127, p. 109513, 2021.

UO for bearing measurements

Lemma (Uniform observability)

(A, C(t)) is uniformly observable if there exist $\delta, \mu > 0$ such that for all $t \ge 0$ one has

$$rac{1}{\delta}\int_t^{t+\delta}\sum_{i=1}^n\Pi(R_ib_i(s))ds\geq \mu I_3.$$

Hamel, Tarek, and Claude Samson. "Position estimation from direction or range measurements." Automatica 82 (2017): 137-144.

- **Single camera:** Vehicle is never static nor moving on a straight line passing through the camera.
- **Two cameras:** Vehicle not aligned (indefinitely) with both cameras.
- Three cameras or more: If at least 3 cameras are not aligned, the observability condition is always satisfied.

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UO for bearing measurements+ Altimeter

• An altimeter is a sensor that measures the altitude

$$y = \begin{bmatrix} C_p(t) \\ e_3^\top \end{bmatrix} p.$$

UO for bearing measurements+ Altimeter

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(A, C(t)) is uniformly observable if there exist $\delta, \mu > 0$ such that for all $t \ge 0$ one has

$$\frac{1}{\delta}\int_t^{t+\delta}\sum_{i=1}^n \Pi(R_ib_i(s))ds + e_3e_3^\top \ge \mu I_3.$$

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UO for bearing measurements+ Altimeter

• An altimeter is a sensor that measures the altitude

$$y = \begin{bmatrix} C_p(t) \\ e_3^\top \end{bmatrix} p.$$

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(A, C(t)) is uniformly observable if there exist $\delta, \mu > 0$ such that for all $t \ge 0$ one has

$$\frac{1}{\delta}\int_t^{t+\delta}\sum_{i=1}^n\Pi(R_ib_i(s))ds+e_3e_3^\top\geq\mu I_3.$$

- Single camera + altimeter: Vehicle not moving at the same altitude as the camera or, if doing so, not moving on a straight line passing through the camera
- **Two cameras** + altimeter: Cameras not at the same altitude. If the cameras are at the same altitude, vehicle must not be aligned (indefinitely) with both cameras.

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Application: Pose Estimation

Simulations: single bearing



Figure 4: Observability holds but slow convergence.

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Application: Pose Estimation

Simulations: single bearing + altimeter



Figure 5: Stronger observability.

Universal Observers: Inertial-Frame Position Information Experimental results





at University of Nice Sophia Antipolis

S. Berkane, A. Tayebi, and S. De Marco, "A nonlinear navigation observer using imu and generic position information," Automatica, vol. 127, p. 109513, 2021.

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Conclusion

Inertial Navigation Systems

Vision-Aided Inertial Navigation Systems (VINS)



Vision-Aided Inertial Navigation

- Useful in GPS-denied environments
- Information on the surrounding environment



• Body-frame landmark position measurements:

$$y_i = R^{\top}(p_i - p), \quad i = 1, \dots, N$$

with at least $N \ge 3$ non-collinear landmarks

Inertial Navigation Systems

Vision-Aided Inertial Navigation Systems (VINS): Stereo vs. Monocular



Figure 6: (a) monocular vision system (b) stereo vision system.

remark

Landmark positions can be algebraically reconstructed from stereo-bearing measurements. The direct use of the stereo-bearing measurements gives **robustness** in situations where one of the cameras of the stereo-vision system loses sight of the landmarks for some period of time.

S. Berkane (UQO)

Application: Pose Estimation

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Vision-Aided Inertial Navigation Systems (VINS): Stereo vs. Monocular

Let p_i denote the (constant and known) position of the *i*-th landmark in frame $\{\mathcal{I}\}$, and

$$p_i^{\mathcal{B}} := R^{\top}(p_i - p)$$

denote the position of the *i*-th landmark in frame $\{B\}$

1) Stereo-bearing measurements:

$$y_{i}^{s} := \frac{p_{i}^{C_{s}}}{\|p_{i}^{C_{s}}\|} = \frac{R_{cs}^{\top}(p_{i}^{\mathcal{B}} - p_{cs})}{\|p_{i}^{\mathcal{B}} - p_{cs}\|}, \ i \in \{1, 2, \dots, N\}, s \in \{1, 2\}$$
(21)

where $p_i^{C_s} = R_{cs}^{\top}(p_i^{\mathcal{B}} - p_{cs}).$

2) Monocular-bearing measurements:

$$y_{i} := \frac{p_{i}^{\mathcal{C}}}{\|p_{i}^{\mathcal{C}}\|} = \frac{R_{c}^{\top}(p_{i}^{\mathcal{B}} - p_{c})}{\|p_{i}^{\mathcal{B}} - p_{c}\|}, \ i \in \{1, 2, \dots, N\}$$
(22)

where $p_i^{\mathcal{C}} = R_c^{\top}(p_i^{\mathcal{B}} - p_c).$

Inertial-Frame Kinematics



Figure 7: Structure of the proposed nonlinear observer on $SO(3) \times \mathbb{R}^{15}$ for vision-aided INS.

remark

The auxiliary signals \hat{e}_1 , \hat{e}_2 , \hat{e}_3 are introduced to help construct the attitude innovation term due to the lack of known inertial-frame vectors (in the case of bearing measurements).

$$\hat{R} = \hat{R}(\omega + \hat{R}^{\top}\sigma_R)^{\times}$$
 (23a)

$$\dot{\hat{\rho}} = \hat{v} + \sigma_R^{\times} \hat{\rho} + \hat{R} K_\rho \sigma_y$$
 (23b)

$$\dot{\hat{v}} = \hat{g} + \hat{R}a + \sigma_R^{\times}\hat{v} + \hat{R}K_v\sigma_y$$
(23c)

$$\dot{\hat{e}}_i = \sigma_R^{\times} \hat{e}_i + \hat{R} K_i \sigma_y, \quad i = 1, 2, 3$$
(23d)

The attitude innovation term σ_R is given as follows:

$$\sigma_{R} := \frac{k_{R}}{2} \hat{R} \sum_{i=1}^{3} \rho_{i} (\hat{R}^{\top} \hat{e}_{i})^{\times} (\hat{R}^{\top} e_{i}) = \frac{k_{R}}{2} \sum_{i=1}^{3} \rho_{i} \hat{e}_{i}^{\times} e_{i}$$
(24)

The gain matrices $K_p, K_v, K_i \in \mathbb{R}^{3 \times 3}, i = 1, 2, 3$ are designed as follows:

$$K = PC^{\top}(t)Q(t) = [K_{\rho}^{\top}, K_{1}^{\top}, K_{2}^{\top}, K_{3}^{\top}, K_{\nu}^{\top}]^{\top}$$
(25)

The matrix P is the solution to the following CRE:

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$$\dot{P} = A(t)P + PA^{\top}(t) - PC^{\top}(t)Q(t)C(t)P + V(t)$$
(26)
(VQ0)
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$$A(t) = \begin{bmatrix} -\omega^{\times} & 0_{3} & 0_{3} & 0_{3} & l_{3} \\ 0_{3} & -\omega^{\times} & 0_{3} & 0_{3} & 0_{3} \\ 0_{3} & 0_{3} & -\omega^{\times} & 0_{3} & 0_{3} \\ 0_{3} & 0_{3} & 0_{3} & -\omega^{\times} & 0_{3} \\ 0_{3} & g_{1}l_{3} & g_{2}l_{3} & g_{3}l_{3} & -\omega^{\times} \end{bmatrix}.$$
 (27)

From the monocular-bearing measurements, vector σ_{yi} is designed as

$$\sigma_{yi} = \Pi(R_c y_i)(\hat{R}^\top(\hat{p}_i - \hat{p}) - p_c)$$
(28)

with $\Pi_i := \Pi(R_c y_i) \in \mathbb{R}^{3 \times 3}, i \in \{1, \dots, N\}$. The matrix C(t) is given by:

$$C(t) = \begin{bmatrix} \Pi_{1} & -p_{11}\Pi_{1} & -p_{12}\Pi_{1} & -p_{13}\Pi_{1} & 0_{3} \\ \Pi_{2} & -p_{21}\Pi_{2} & -p_{22}\Pi_{2} & -p_{23}\Pi_{2} & 0_{3} \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ \Pi_{N} & -p_{N1}\Pi_{N} & -p_{N2}\Pi_{N} & -p_{N3}\Pi_{N} & 0_{3} \end{bmatrix}$$
(29)

S. Berkane (UQO)

• The proof of AGAS is based on the following geometric errors

$$\begin{split} \tilde{R} &= R\hat{R}^{\top} \in SO(3) \\ \tilde{p} &= R^{\top}p - \hat{R}^{\top}\hat{p} \\ \tilde{v} &= R^{\top}v - \hat{R}^{\top}\hat{v} \\ \tilde{e}_{i} &= R^{\top}e_{i} - \hat{R}^{\top}\hat{e}_{i}, \forall i \in \{1, 2, 3\} \end{split}$$
with $\tilde{x} := [\tilde{p}^{\top}, \tilde{e}_{1}^{\top}, \tilde{e}_{2}^{\top}, \tilde{e}_{3}^{\top}, \tilde{v}^{\top}]^{\top} \in \mathbb{R}^{15}$

remark

The projection operator $\Pi(R_c y_i)$ allows to eliminate the component which is collinear to $R_c y_i$. The projection of $\hat{R}^{\top}(\hat{p}_i - \hat{p}) - p_c$ onto the plane orthogonal to $R_c y_i$ will boil down to the projection of $\hat{R}^{\top}(\hat{p}_i - \hat{p}) - p_i^{\mathcal{B}}$. This mechanism, allow us to **put the error injection vector as** $\sigma_y = C(t)\tilde{x}$.

• One obtains the following closed-loop system:

$$\dot{\tilde{R}} = \tilde{R}(-\psi_{a}(M\tilde{R}) - \Gamma(t)\tilde{x})^{ imes}$$
 (30a)

$$\dot{\tilde{x}} = (A(t) - KC(t))\tilde{x}$$
 (30b)

Theorem

Assume (A(t), C(t)) is uniformly observable. Then:

 i) All solutions of the closed-loop system (30) converge to the set of equilibria given by (I₃, 0_{15×1}) ∪ Ψ_M where

$$\Psi_{\mathcal{M}} := \{ (\tilde{R}, \tilde{x}) \in SO(3) \times \mathbb{R}^{15} | \tilde{R} = \mathcal{R}_{\alpha}(\pi, \nu), \nu \in \mathcal{E}(\mathcal{M}), \tilde{x} = \mathbf{0}_{15 \times 1} \}.$$

- ii) The desired equilibrium $(I_3, 0_{15 \times 1})$ is locally exponentially stable.
- iii) All the undesired equilibria in Ψ_M are unstable, and the desired equilibrium $(I_3, 0_{15\times 1})$ is almost globally asymptotically stable.

Universal Observers: Body-Frame Position Information Inertial-Frame Kinematics: Observability Analysis

Monocular camera in motion

- there exist three non-aligned landmarks whose plane is not parallel to the gravity vector
- the camera is regularly not aligned with the same landmark



Motionless monocular camera

Application: Pose Estimation

M. Wang, S. Berkane, and A. Tayebi, "Nonlinear observers design for vision-aided inertial navigation systems," IEEE Transactions on Automatic Control, vol. 67, no. 4, pp. 1853–1868, 2021.

Inertial-Frame Kinematics: Observability Analysis



Motionless monocular camera



Inertial-Frame Kinematics: Experimental Results

EuRoc dataset:

- The trajectories are generated from a real quadrotor flight
- The EuRoc dataset includes a set of stereo images (20Hz) and IMU measurements (200Hz)
- The ground truth is obtained from Vicon motion capture system



Inertial-Frame Kinematics: Experimental Results

• **Stereo-Bearings** position error $\approx 3.26cm$

• Monocular-Bearings position error $\approx 10.99 cm$

M. Wang, S. Berkane, and A. Tayebi, "Nonlinear observers design for vision-aided inertial navigation systems," IEEE Transactions on Automatic Control, vol. 67, no. 4, pp. 1853–1868, 2021.

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Application: Pose Estimation

Model with body-frame states

$$\dot{\boldsymbol{\rho}}^{\mathcal{B}} = -[\boldsymbol{\omega}]_{\times} \boldsymbol{\rho}^{\mathcal{B}} + \boldsymbol{v}^{\mathcal{B}},\tag{31}$$

$$\dot{\boldsymbol{v}}^{\mathcal{B}} = -[\boldsymbol{\omega}]_{\times} \boldsymbol{v}^{\mathcal{B}} + \boldsymbol{a}^{\mathcal{B}} + \sum g_i \boldsymbol{e}_i^{\mathcal{B}}, \qquad (32)$$

$$\dot{e}_1^{\mathcal{B}} = -[\omega]_{\times} e_1^{\mathcal{B}},\tag{33}$$

$$\dot{\mathbf{e}}_{2}^{\mathcal{B}} = -[\boldsymbol{\omega}]_{\times} \mathbf{e}_{2}^{\mathcal{B}}, \tag{34}$$
$$\dot{\boldsymbol{\beta}}_{\mathcal{B}} = [\boldsymbol{\omega}]_{\times} \mathbf{e}_{2}^{\mathcal{B}}, \tag{35}$$

$$\dot{e}_3^{\mathcal{B}} = -[\omega]_{\times} e_3^{\mathcal{B}}.\tag{35}$$

• Let us now introduce the following virtual output:

$$y := \begin{bmatrix} \Pi_1(p^{\mathcal{B}} - p_1^{\mathcal{B}}) \\ \vdots \\ \Pi_N(p^{\mathcal{B}} - p_N^{\mathcal{B}}) \end{bmatrix} = \begin{bmatrix} \mathbf{0}_{3 \times 1} \\ \vdots \\ \mathbf{0}_{3 \times 1} \end{bmatrix}$$
(36)

Define the following state vector

$$x = \begin{bmatrix} (\boldsymbol{p}^{\mathcal{B}})^{\top} & (\boldsymbol{e}_{1}^{\mathcal{B}})^{\top} & (\boldsymbol{e}_{2}^{\mathcal{B}})^{\top} & (\boldsymbol{e}_{3}^{\mathcal{B}})^{\top} & (\boldsymbol{v}^{\mathcal{B}})^{\top} \end{bmatrix}^{\top}, \quad (37)$$

• We obtain an LTV system of the form:

$$\dot{x} = A(t)x + Ba^{\mathcal{B}},$$
 (38a)
 $y = C(t)x,$ (38b)

with matrices A(t), B and C(t) defined previously.

• The state of system is then estimated using the Riccati observer:

$$\dot{\hat{x}} = A(t)\hat{x} + Ba^{\mathcal{B}} + K(t)(y - C(t)\hat{x}),$$
(39)

Theorem

If (A(t), C(t)) is UO then we have UGES.

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The orientation matrix can be computed using algebraic reconstruction

$$\hat{\mathsf{R}}^{\top} = \begin{bmatrix} \hat{e}_2^{\mathcal{B}} \times \hat{e}_3^{\mathcal{B}} & \hat{e}_3^{\mathcal{B}} \times (\hat{e}_2^{\mathcal{B}} \times \hat{e}_3^{\mathcal{B}}) & \hat{e}_3^{\mathcal{B}} \end{bmatrix}, \tag{40}$$

• \hat{R} is then projected on SO(3) using polar decomposition

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P. Martin and I. Sarras, "A global observer for attitude and gyro biases from vector measurements," 20th IFAC World Congress,, 2017.

- This approach allows the use of any attitude reconstruction/estimation algorithm.
- For example, one can use a complementary filter on *SO*(3) to recover the attitude with AGAS result:

$$\begin{cases} \dot{\hat{R}} &= \hat{R}[\omega + \sigma_R]_{\times}, \\ \sigma_R &= \sum \rho_i (\hat{e}_i^{\mathcal{B}} \times \hat{R}^{\top} e_i) \end{cases}$$

• This approach can be tailored to double or even single bearing measurements

S.-E. Benahmed and S. Berkane, "State estimation using single body-frame bearing measurements," in *European Control* Conference, 2024.

Concluding Remarks

Body-Frame Input (IMU)

Inertial-Frame Position

Information

Body-Frame Position

Information

Inertial-Frame Kinematics

Body-Frame Kinematics

Euclidean Errors

Geometric Errors

Concluding Remarks


Concluding Remarks



Concluding Remarks

Body-Frame Input (IMU)



Thank you

Questions?