Visual-Inertial-Aided Online MAV System Identification

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Introduction

- **<u>Online</u>** system **parameters identification** for micro aerial vehicles (MAV)
- **<u>Crucial</u>**:
  - Model-based control tasks require accurate system parameters
  - Online estimate platform reconfiguration (e.g. payload and environmental effects)
- **<u>Challenging</u>**:
  - High-dynamic motion and under-actuation exacerbate state estimation
  - Efficient, light-weight, resource-constrained estimator for online system identification

<u>Contributions:</u>

- Numerical **analysis** for MAV dynamics and online system identification
  - EKF-based fusion hurt the motion estimation and parameter identification performance due to the model imperfection
- Novel **tightly-coupled Schmidt Kalman filter (SKF)-based visual inertial** estimator
  - **Online** estimate MAV-IMU extrinsic, MAV aerodynamic (e.g. thrust coef.), and geometrical parameters (e.g. mass) **accurately**
- Validated in **simulation** and **real-world** experiments

MAV Dynamics

- Rotor speed input $r_i = r_{m,i} - n_{r,i}$

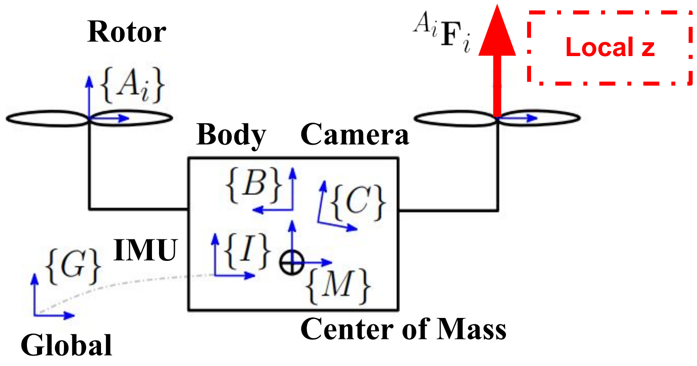
Single Force $\quad {}^{A_i}\mathbf{F}_i = c_t r_i^2 \mathbf{e}_z$

Single Moment $\quad {}^{A_i}\mathbf{M}_i = c_m r_i^2 \lambda_i \mathbf{e}_z$

Total $\rightarrow$

$$ {}^{M}\mathbf{F} = \sum_{i=1}^{N_r} {}^{M}_{A_i}\mathbf{R}\, {}^{A_i}\mathbf{F}_i $$

$$ {}^{M}\mathbf{M} = \sum_{i=1}^{N_r} \left({}^{M}_{A_i}\mathbf{R}\, {}^{A_i}\mathbf{M} + \lfloor {}^{M}_{B}\mathbf{R}\, {}^{B}\mathbf{p}_{A_i} + {}^{M}\mathbf{p}_B \rfloor\, {}^{M}\mathbf{F}_i \right) $$



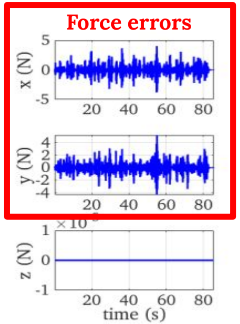
- MAV Newton-Euler equations

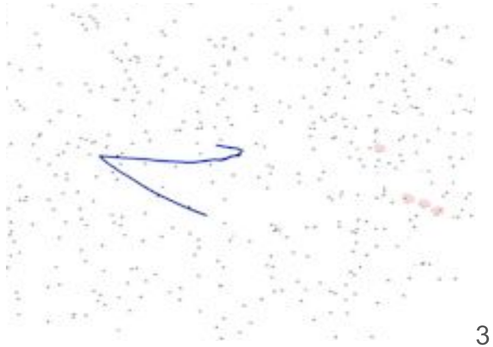
$$
\begin{array}{r}
\text{Rotation} \\
\text{Position} \\
\text{Angular velocity} \\
\text{Linear velocity}
\end{array}
\begin{bmatrix} {}^{M}_{G}\dot{\bar{q}} \\ {}^{G}\dot{\mathbf{p}}_M \\ {}^{M}\dot{\boldsymbol{\omega}} \\ {}^{G}\dot{\mathbf{v}}_M \end{bmatrix}
=
\begin{bmatrix} \frac{1}{2}\boldsymbol{\Omega}\left({}^{M}\boldsymbol{\omega}\right) {}^{M}_{G}\bar{q} \\ {}^{G}\mathbf{v}_M \\ {}^{M}\mathbf{J}^{-1}\left({}^{M}\mathbf{M} - \lfloor {}^{M}\boldsymbol{\omega} \rfloor {}^{M}\mathbf{J}\, {}^{M}\boldsymbol{\omega}\right) \\ \frac{1}{m}\, {}^{M}_{G}\mathbf{R}^{\top}\, {}^{M}\mathbf{F} - {}^{G}\mathbf{g} \end{bmatrix}
$$

System Parameters $\mathbf{x}_\theta$

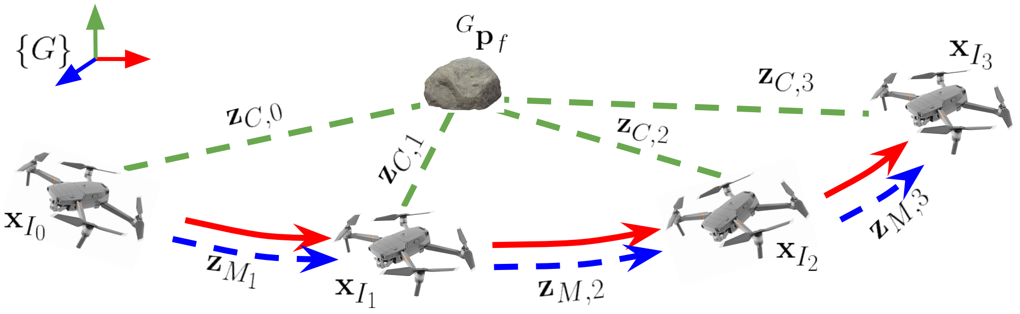
c_t	Thrust coefficient	${}^{M}\mathbf{p}_B$	$\{B\}$ and $\{M\}$ translation
c_m	Moment coefficient	${}^{I}\mathbf{p}_M$	$\{I\}$ and $\{M\}$ translation
m	Mass	${}^{M}_{I}\mathbf{R}$	$\{I\}$ to $\{M\}$ rotation
${}^{M}\mathbf{J}$	Moment of inertia		

- Dynamic model is **widely-used** but does **not capture full force** on platform (inaccurate)
  - Force model can not represent the **true** force
  - Online parameter identification becomes **<u>challenging</u>**
  - Rotor speed measurement noise $n_{r,i}$
  - Model imperfection noise $\mathbf{n}_{f,i}$ $\mathbf{n}_{m,i}$





System Overview



Goal:

- **Online** MAV visual inertial **navigation** and system parameter **identification**
- **Efficiently** incorporate (inaccurate) MAV dynamics to **accurately recover** parameters

Light-weight filter-based solution:

- State vector

$$\mathbf{x}_k = \begin{bmatrix} \mathbf{x}_A \\ \mathbf{x}_\theta \end{bmatrix} \begin{matrix} \text{Active VIO} \\ \text{Parameters} \end{matrix} \qquad \mathbf{x}_A = \begin{bmatrix} \mathbf{x}_{I_k} \\ \mathbf{x}_f \\ \mathbf{x}_C \end{bmatrix} \begin{matrix} \text{IMU Inertial} \\ \text{Feature} \\ \text{Clone} \end{matrix}$$

IMU pose
angular velocity
linear velocity

- Measurement Processing
  1. IMU inertial propagation
  2. Visual features MSCKF update[1]
  3. MAV dynamics update

IMU readings **fully** measure the trajectory
Outlier gating test to **reject** MAV measurements

MAV Dynamic Measurements

- Dynamic model integration

$$\mathbf{x}_{M_{k+1}} = \mathbf{g}_M(\mathbf{x}_{M_k}, \mathbf{x}_\theta, \mathbf{n}_M)$$

- MAV-IMU rigid body transformation

$$\mathbf{x}_{M_k} = \mathbf{h}_{t,k}(\mathbf{x}_A, \mathbf{x}_\theta)$$

- Linearized measurement equation

$$\tilde{\mathbf{z}}_{M_k} = \begin{bmatrix} \mathbf{H}_A & \mathbf{H}_\theta \end{bmatrix} \begin{bmatrix} \tilde{\mathbf{x}}_A \\ \tilde{\mathbf{x}}_\theta \end{bmatrix} - \mathbf{G}_n \mathbf{n}_M$$

[1] Mourikis, Anastasios I., et al "A Multi-State Constraint Kalman Filter for Vision-aided Inertial Navigation." *2007 IEEE International Conference on Robotics and Automation (ICRA)*. IEEE, 2007.

SKF-based Parameter Identification

A: VIO states
θ : parameter states

Standard EKF Update

$$\begin{bmatrix}\mathbf{x}_A^+\\ \mathbf{x}_\theta^+\end{bmatrix} = \begin{bmatrix}\mathbf{x}_A^-\\ \mathbf{x}_\theta^-\end{bmatrix} + \begin{bmatrix}\boxed{\mathbf{L}_A^-}\\ \mathbf{L}_\theta^-\end{bmatrix}\mathbf{S}^{-1}\mathbf{r}$$

$$\begin{bmatrix}\mathbf{P}_{AA}^+ & \mathbf{P}_{A\theta}^+\\ \mathbf{P}_{\theta A}^+ & \mathbf{P}_{\theta\theta}^+\end{bmatrix} = \begin{bmatrix}\mathbf{P}_{AA}^- & \mathbf{P}_{A\theta}^-\\ \mathbf{P}_{\theta A}^- & \mathbf{P}_{\theta\theta}^-\end{bmatrix} - \begin{bmatrix}\boxed{\mathbf{L}_A\mathbf{S}^{-1}\mathbf{L}_A^\top} & \mathbf{L}_A\mathbf{S}^{-1}\mathbf{L}_\theta^\top\\ \mathbf{L}_\theta\mathbf{S}^{-1}\mathbf{L}_A^\top & \mathbf{L}_\theta\mathbf{S}^{-1}\mathbf{L}_\theta^\top\end{bmatrix}$$

- Numerical analysis shows the dynamic is inaccurate
- **MAV dynamic noise** parameters are crucial
- Over-confident dynamic model **hurts** both VIO and parameter identification

σ	RMSE deg / cm	NEES Ori. / Pos.
0.05	2.81 / 525.9	1543.21 / 65.68
0.50	1.14 / 1.9	31.49 / 4.37
1.00	0.74 / 1.9	2.40 / 3.15
1.50	0.71 / 1.9	2.28 / 3.30

Hurt VIO

Schmidt-EKF (SKF) Update

$$\begin{bmatrix}\mathbf{x}_A^+\\ \mathbf{x}_\theta^+\end{bmatrix} = \begin{bmatrix}\mathbf{x}_A^-\\ \mathbf{x}_\theta^-\end{bmatrix} + \begin{bmatrix}\boxed{\mathbf{0}}\\ \mathbf{L}_\theta^-\end{bmatrix}\mathbf{S}^{-1}\mathbf{r}$$

$$\begin{bmatrix}\mathbf{P}_{AA}^+ & \mathbf{P}_{A\theta}^+\\ \mathbf{P}_{\theta A}^+ & \mathbf{P}_{\theta\theta}^+\end{bmatrix} = \begin{bmatrix}\mathbf{P}_{AA}^- & \mathbf{P}_{A\theta}^-\\ \mathbf{P}_{\theta A}^- & \mathbf{P}_{\theta\theta}^-\end{bmatrix} - \begin{bmatrix}\boxed{\mathbf{0}} & \mathbf{L}_A\mathbf{S}^{-1}\mathbf{L}_\theta^\top\\ \mathbf{L}_\theta\mathbf{S}^{-1}\mathbf{L}_A^\top & \mathbf{L}_\theta\mathbf{S}^{-1}\mathbf{L}_\theta^\top\end{bmatrix}$$

- **Protecting** VIO, MAV measurements **only** update MAV related parameters
- **Visual meas. applied** with **standard** EKF
- Track **correlations** refine parameters

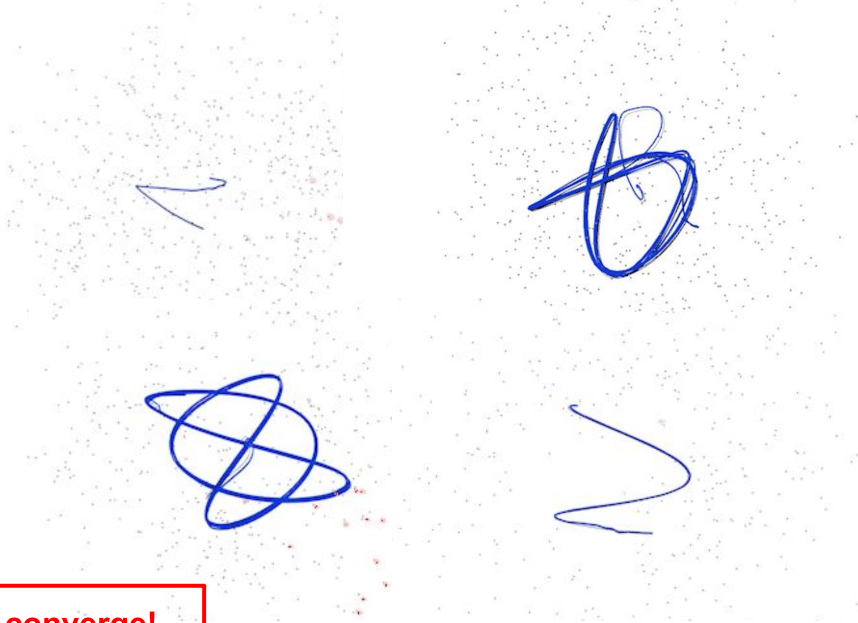
σ	RMSE deg / cm	NEES Ori. / Pos.	$\tilde{c}_t$	$\tilde{c}_m$	${}^M\tilde{\mathbf{p}}_B$	${}^I_M\delta\boldsymbol{\theta}$	${}^I\tilde{\mathbf{p}}_M$
0.05	0.75 / 1.84	2.20 / 2.69	2.3e-08	1.3e-08	3.2e-05	0.1	1.4e-03
0.50	0.75 / 1.84	2.20 / 2.69	2.8e-08	7.9e-08	5.2e-05	0.4	1.3e-03
1.00	0.75 / 1.84	2.20 / 2.69	3.2e-08	2.5e-07	1.5e-04	1.0	1.3e-03
1.50	0.75 / 1.84	2.20 / 2.69	3.7e-08	4.0e-07	3.2e-04	1.3	1.4e-03

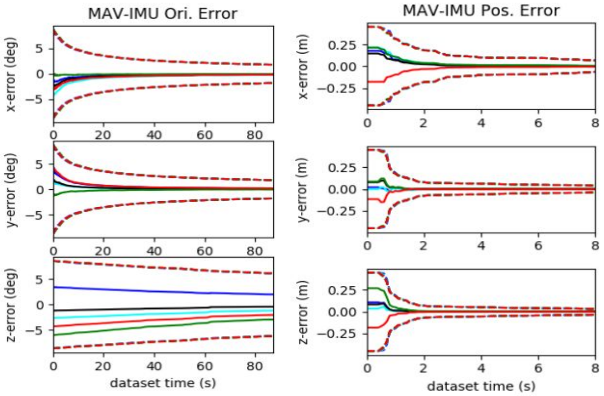
Protect VIO **Accurate Calibration**

Monte-Carlo Simulations

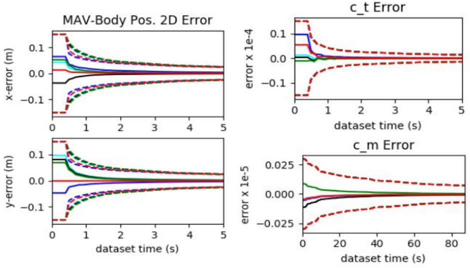
- **IMU**, **camera**, **rotor readings, MAV configurations** simulated with OpenVINS[1], trajectories generated with RotorS[2]

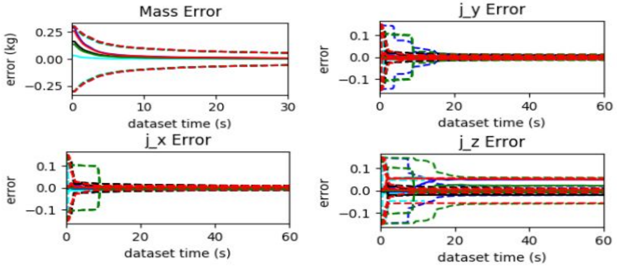
Parameter	Value	Parameter	Value	Parameter	Value
IMU Freq. (hz)	200	${}^{B}\mathbf{p}_{A_1}$ (m)	0.21, 0.00, 0.05	${}^{I}_{M}\bar{q}$	0, 0, 0, 1
Cam Freq. (hz)	10	${}^{B}\mathbf{p}_{A_2}$ (m)	0.00, 0.21, 0.05	${}^{I}\mathbf{p}_{M}$ (m)	0, 0, 0
Rotor Freq. (hz)	300	${}^{B}\mathbf{p}_{A_3}$ (m)	-0.21, 0.00, 0.05	${}^{M}\mathbf{p}_{B}$ (m)	0, 0, 0
Pixel Noise (pix)	1	${}^{B}\mathbf{p}_{A_4}$ (m)	0.00, -0.21, 0.05	c_t (N s^2/rad^2)	9.9865e-06
Rotor White Noise (rad/s)	0.043	λ_1,λ_2,λ_3,λ_4	1, -1, 1, -1	c_m (N s^2/rad^2)	1.455784e-7
Gyro. White Noise	1.6968e-4	Accel. Rand. Walk	3.0000e-2	${}^{M}\mathbf{j}$	0.01, 0.01, 0.02
Accel. White Noise	2.0000e-2	Gyro. Rand. Walk	1.9393e-4	Mass (kg)	1





Parameters quickly converge!





[1] Geneva, Patrick, et al. "Openvins: A research platform for visual-inertial estimation." *2020 IEEE International Conference on Robotics and Automation (ICRA)*. IEEE, 2020.
[2] Furrer, Fadri, et al. "RotorS—a modular gazebo mav simulator framework." *Robot operating system (ROS)*, 2016.

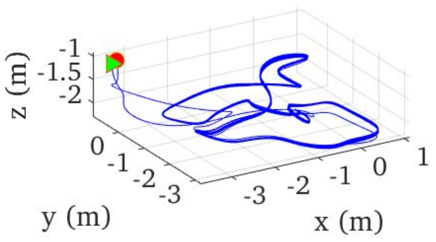
Real-world: Blackbird Dataset

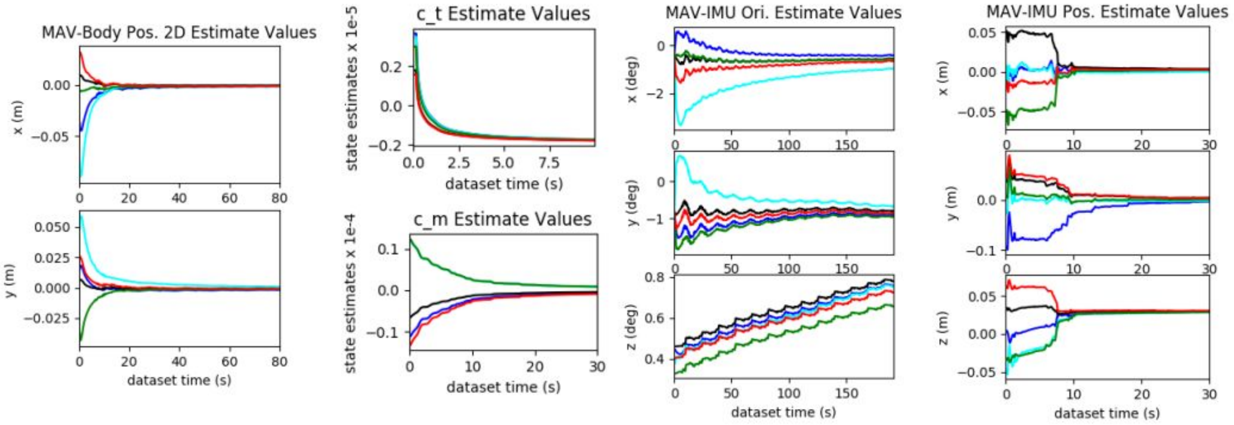
- Proposed SKF trajectory has same accuracy as OpenVINS (as expected)
- EKF parameter identification can perform after **tuning** of noise parameters
- SKF is **robust** to **model errors** and ensures accurate parameter identification

More dynamic motion!

Algorithm	RMSE (1 m/s)	RMSE (2 m/s)	RMSE (3 m/s)
Proposed EKF	1.463 / 0.067	1.696 / 0.119	4.195 / 0.703
Proposed SKF	1.571 / 0.069	1.703 / 0.120	3.881 / 0.720
OpenVINS [1]	1.571 / 0.069	1.703 / 0.120	3.881 / 0.720
VINS-Mono [2]	1.281 / 0.075	2.851 / 0.515	4.598 / 0.965

Parameters quickly converge!





[1] Geneva, Patrick, et al. "Openvins: A research platform for visual-inertial estimation." *2020 IEEE International Conference on Robotics and Automation (ICRA)*. IEEE, 2020.
[2] Qin, Tong, et al. "Vins-mono: A robust and versatile monocular visual-inertial state estimator." *IEEE Transactions on Robotics (TRO)*. IEEE, 2018.

Summary & Thanks!

Conclusion:

- Investigated MAV dynamic model, EKF-based fusion, shown to **degrade** performance
- Tightly-coupled real-time **SKF-based** estimator
  - **Protects** consistent motion estimation (VIO)
  - Ensures **accurate** and **robust** online parameter identification
- Demonstrate the performance with **simulations** and **real-world** datasets

Where next?

- Integrate and evaluate the proposed estimator with fully autonomous system
- Degenerate motion analysis and observability-aware motion planning

RPNG

Thank you!

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