NRI: FND: Consistent Distributed Visual-Inertial Estimation and Perception for Cooperative Unmanned Aerial Vehicles

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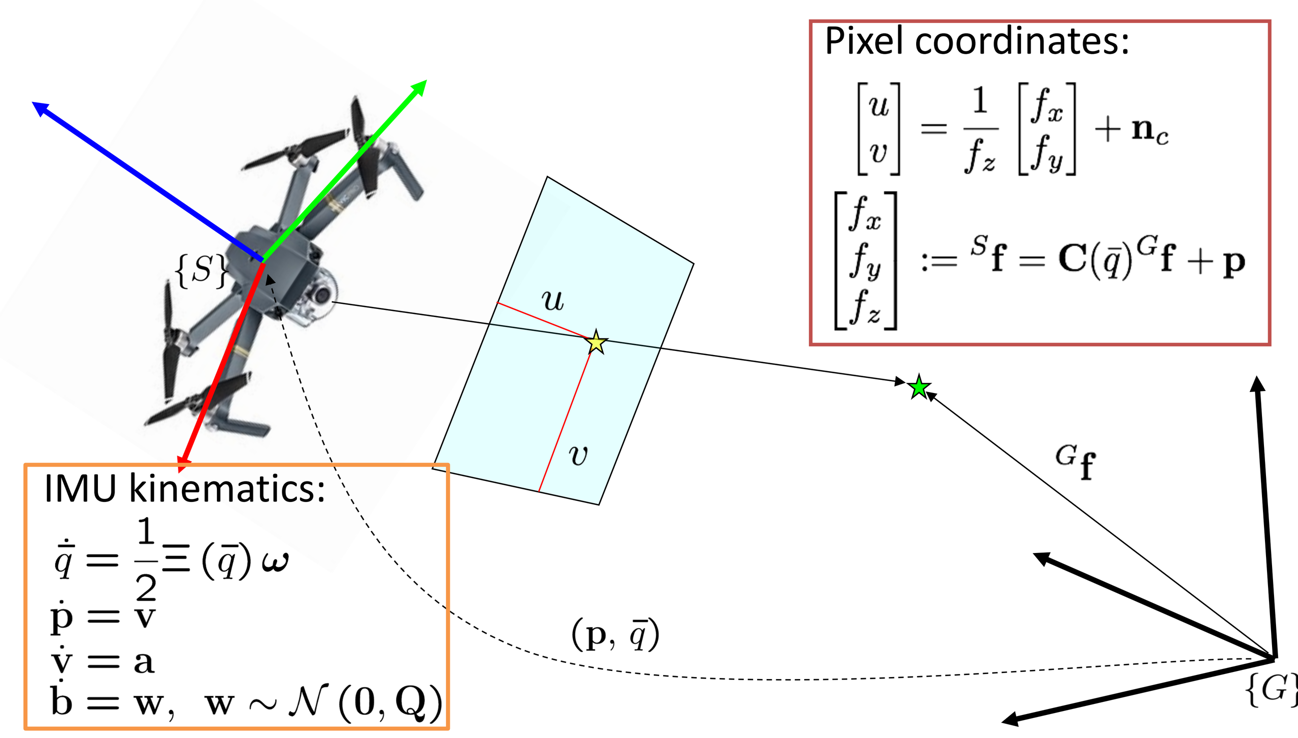
https://sites.udel.edu/robot/

1. Visual-inertial estimation

- Visual-inertial navigation system (VINS) or SLAM holds great potentials in practical applications:

- Goal: To estimate 3D motion & scene understanding using IMUs and cameras onboard unmanned aerial vehicles (UAVs)

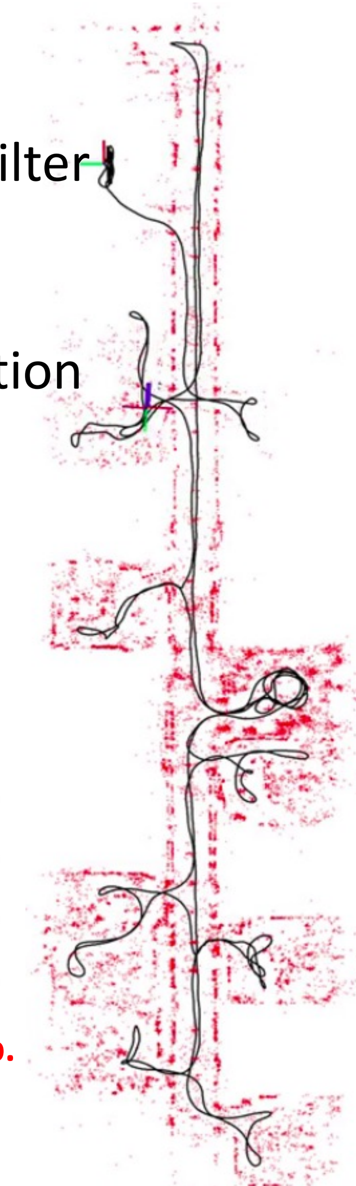


- **Technical challenges when extending to multi-UAVs:**
  - ❑ Consistent, distributed, cooperative visual-inertial estimation under resource constraints

2. OpenVINS: A Research Platform for Visual-Inertial Estimation [IROS2021]

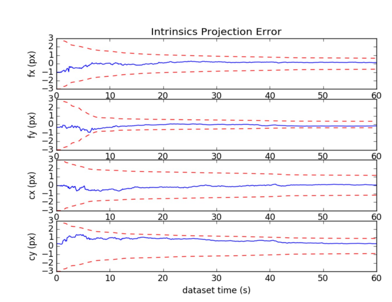
Key Features:

- On manifold sliding window visual-inertial Kalman filter with modular **type system** for state management
- **Online** camera and IMU **calibration**
- **First-Estimate Jacobians (FEJ)** for consistent estimation
- Five different feature representation methods
- Static and dynamic state initialization
- Extendable visual-inertial **simulator** and extensive toolbox for algorithm evaluation and plotting



	V1_01_easy	V1_02_medium	V1_03_difficult	V2_01_easy	V2_02_medium	Average
mono_ov_slam	0.699 / 0.058	1.675 / 0.076	2.542 / 0.063	0.773 / 0.124	1.538 / 0.074	1.445 / 0.079
mono_ov_vio	0.642 / 0.076	1.766 / 0.096	2.391 / 0.344	1.164 / 0.121	1.248 / 0.106	1.442 / 0.148
mono_okvis	0.823 / 0.090	2.082 / 0.146	4.122 / 0.222	0.826 / 0.117	1.704 / 0.197	1.911 / 0.154
mono_rovioli	2.249 / 0.153	1.635 / 0.131	3.253 / 0.158	1.455 / 0.106	1.678 / 0.153	2.054 / 0.140
mono_rvio	0.994 / 0.094	2.288 / 0.129	1.757 / 0.147	1.735 / 0.144	1.690 / 0.233	1.693 / 0.149
mono_vinsfusion_vio	1.199 / 0.064	3.542 / 0.103	5.934 / 0.202	1.585 / 0.073	2.370 / 0.079	2.926 / 0.104
stereo_ov_slam	0.856 / 0.061	1.813 / 0.047	2.764 / 0.059	1.037 / 0.056	1.292 / 0.047	1.552 / 0.054
stereo_ov_vio	0.905 / 0.061	1.767 / 0.056	2.339 / 0.057	1.106 / 0.053	1.151 / 0.048	1.454 / 0.055
stereo_basalt	0.654 / 0.035	2.067 / 0.059	2.017 / 0.085	0.981 / 0.046	0.888 / 0.059	1.321 / 0.057
stereo_iceba	0.909 / 0.059	2.574 / 0.120	3.206 / 0.137	1.819 / 0.128	1.212 / 0.116	1.944 / 0.112
stereo_okvis	0.603 / 0.039	1.963 / 0.079	4.117 / 0.122	0.834 / 0.075	1.201 / 0.092	1.744 / 0.081
stereo_smsckf	1.108 / 0.086	2.147 / 0.121	3.918 / 0.198	1.181 / 0.083	2.142 / 0.164	2.099 / 0.130
stereo_vinsfusion_vio	1.073 / 0.054	2.695 / 0.089	3.643 / 0.132	2.499 / 0.071	2.006 / 0.074	2.383 / 0.084

OpenVINS outperforms SOTA systems!



Online intrinsics calib.

Extensions:

- **ov_plane -** A real-time monocular VIO leverage environmental planes
- **ov_secondary –** Secondary pose graph
- **ov_mapping –** Multi-session mapping
- **vicon2gt –** Ground truth gen. for VIO eval.

Please checkout OpenVINS!
https://github.com/rpng/open_vins
https://docs.openvins.com/

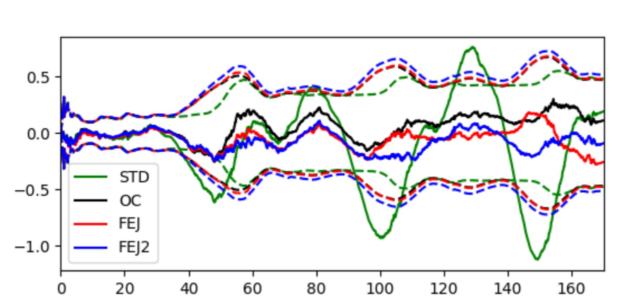
3. FEJ2: A Consistent Visual-Inertial State Estimator Design [ICRA2022]

- Filter-based VINS is inconsistent due to the information gain along unobservable directions
- First-Estimate Jacobian (FEJ) improves consistency and shown impressive performance but introduce **unmodelled errors**
- **FEJ2:** model and address the unmodelled errors to improve both **consistency and accuracy**
- **Key ideas:** Derive a more accurate linear model to **compensate the unmodelled errors** of FEJ

$$\mathbf{r} = \mathbf{z} - \mathbf{h}(\hat{\mathbf{x}}) = \bar{\mathbf{H}}\tilde{\mathbf{x}} + \Delta\mathbf{H}\tilde{\mathbf{x}} + \mathbf{n}$$
$$\Delta\mathbf{U}^\top\mathbf{r} = \Delta\mathbf{U}^\top\bar{\mathbf{H}}\tilde{\mathbf{x}} + \cancel{\Delta\mathbf{U}^\top\Delta\mathbf{H}\tilde{\mathbf{x}}} + \Delta\mathbf{U}^\top\mathbf{n}$$
$$\mathbf{r}^* = \mathbf{H}^*\tilde{\mathbf{x}} + \mathbf{n}^*$$

ΔH captures the errors of using the first-estimate Jacobians for update which is **ignored by FEJ**!

- **Extensive simulation and real-world experiments:**
- Standard estimator is inconsistent
- FEJ2 achieve the **smallest error** and **most ideal** NEES values



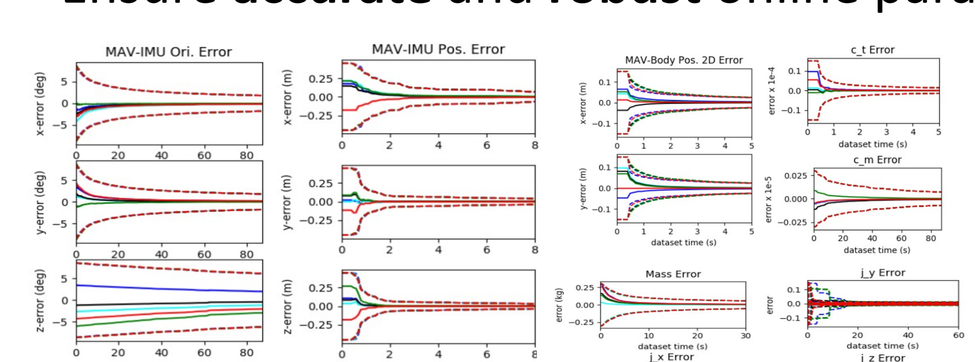
The 3-sigma bound of FEJ2 is broader

Noise (pixel)	Est.	RMSE Ori. (deg) mono / stereo	RMSE Pos. (m) mono / stereo	NEES Ori. mono / stereo	NEES Pos. mono / stereo
1	STD	0.412 / 0.344	0.130 / 0.109	23.874 / 15.447	4.911 / 4.874
	OC	0.242 / 0.257	0.119 / 0.100	3.290 / 3.599	3.540 / 3.416
	FEJ	0.242 / 0.256	0.120 / 0.100	3.284 / 3.438	3.617 / 3.322
	FEJ2	**0.238 / 0.238**	**0.118 / 0.095**	**3.150 / 3.324**	**3.443 / 2.965**
3	STD	2.139 / 0.888	0.402 / 0.310	407.221 / 33.852	13.212 / 7.235
	OC	0.716 / 0.723	0.301 / 0.300	3.964 / 4.395	5.051 / 4.839
	FEJ	0.861 / 0.704	0.289 / 0.298	4.965 / 4.163	4.763 / 4.656
	FEJ2	**0.650 / 0.663**	**0.264 / 0.277**	**3.198 / 3.790**	**3.581 / 3.636**

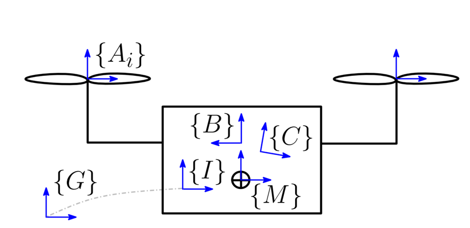
FEJ2 has better accuracy and consistency especially under large measurement noise

4. Online MAV parameter Identification [IROS 2022]

- Novel **tightly-coupled Schmidt Kalman filter (SKF)**-based visual inertial estimator to identify MAV parameters **online**
- Protects **consistent** motion estimation (VIO)
- Ensure **accurate** and **robust** online parameter identification



Parameters quickly converge!



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		

5. Distributed Cooperative Localization [IROS 2021]

- Visual-Inertial Cooperative Localization (CL) can improve localization accuracy
- Distributed method is more **scalable, robust, and efficient** than centralized
- **Our approach**: An efficient distributed state estimator for multi-robot CL which does not require simultaneous viewing of the common features:
  - ❑ Consistent estimation w/ Covariance Intersection (CI)
  - ❑ Efficient common SLAM and VIO feature updates
  - ❑ Historical loop-closure matching across time and robots to reduced drift

Table 1: Relative pose error (RPE) on TUM-VI datasets in degrees / meters averaged over all robots for the dataset.

Algorithm	40m	60m	80m	100m	120m
indp-slam	1.818 / 0.093	2.833 / 0.126	2.604 / 0.154	2.774 / 0.185	2.716 / 0.215
ce-cmsckf	1.358 / 0.071	1.321 / 0.091	1.357 / 0.108	0.843 / 0.128	0.932 / 0.140
ce-cmsckf-cslam	1.758 / 0.069	1.350 /0.079	1.027 / 0.100	0.718 / 0.119	0.938 / 0.130
dc-cmsckf	1.662 / 0.075	2.005 / 0.104	1.605 / 0.129	1.142 / 0.141	1.531 / 0.170
dc-cmsckf-cslam	1.800 / 0.080	2.642 / 0.093	2.233 / 0.106	1.544 / 0.114	0.934 / 0.157
dc-full-window	1.768 / 0.075	2.218 / 0.091	1.788 / 0.109	1.257 / 0.123	0.854 / 0.159
dc-full-history	1.213 / 0.067	1.232 / 0.061	1.029 / 0.065	1.004 / 0.068	0.784 / 0.072

Video Demo
https://www.youtube.com/watch?v=boHBcVoMKk8

Inclusion of common features always **improves** both centralized and decentralized estimators.

Historical matching able to **outperform** all other methods (even the centralized)!

6. Broader impact

- Offer great social benefits by enabling UAVs to work in human non-accessible or unspecified environments
- Foster innovative applications in robotics such as aerial transportation during humanitarian aid and disaster relief, thus boosting economic development
- Promote hands-on learning in undergraduate education and enrich graduate curriculum, and create opportunities for students to perform meaningful robotics research

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