Distributed Visual-Inertial Cooperative Localization

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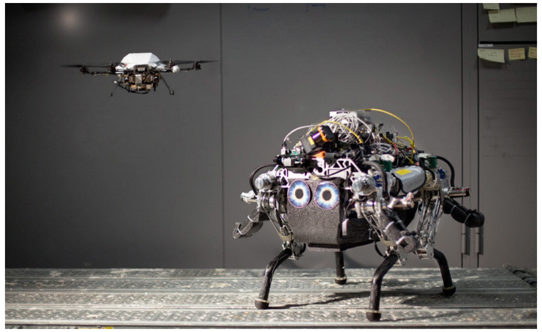
Motivation and Contributions

- Multi-robot systems can **collaborate** to accomplish missions more efficiently and robustly
- Visual-Inertial Cooperative Localization (CL) leveraging **additional geometric constraints** in multi-robot systems can improve the localization accuracy of the whole group
- Distributed estimation algorithms are more **scalable, robust, and efficient** as compared to centralized estimators

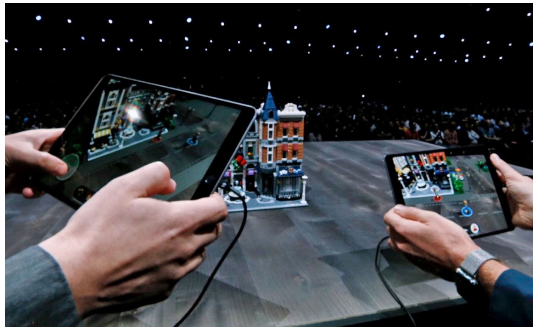
Proposed: An efficient distributed state estimator for multi-robot cooperative localization (CL) which does not require simultaneous viewing of the common features

  - Consistent estimation based on Covariance Intersection (CI)
  - Efficient common SLAM and VIO feature updates
  - Historical loop-closure matching across time and robots to reduced localization drift



Collaborative Navigation
(credit ETH Zurich)

Drone Swarm for Search and Rescue



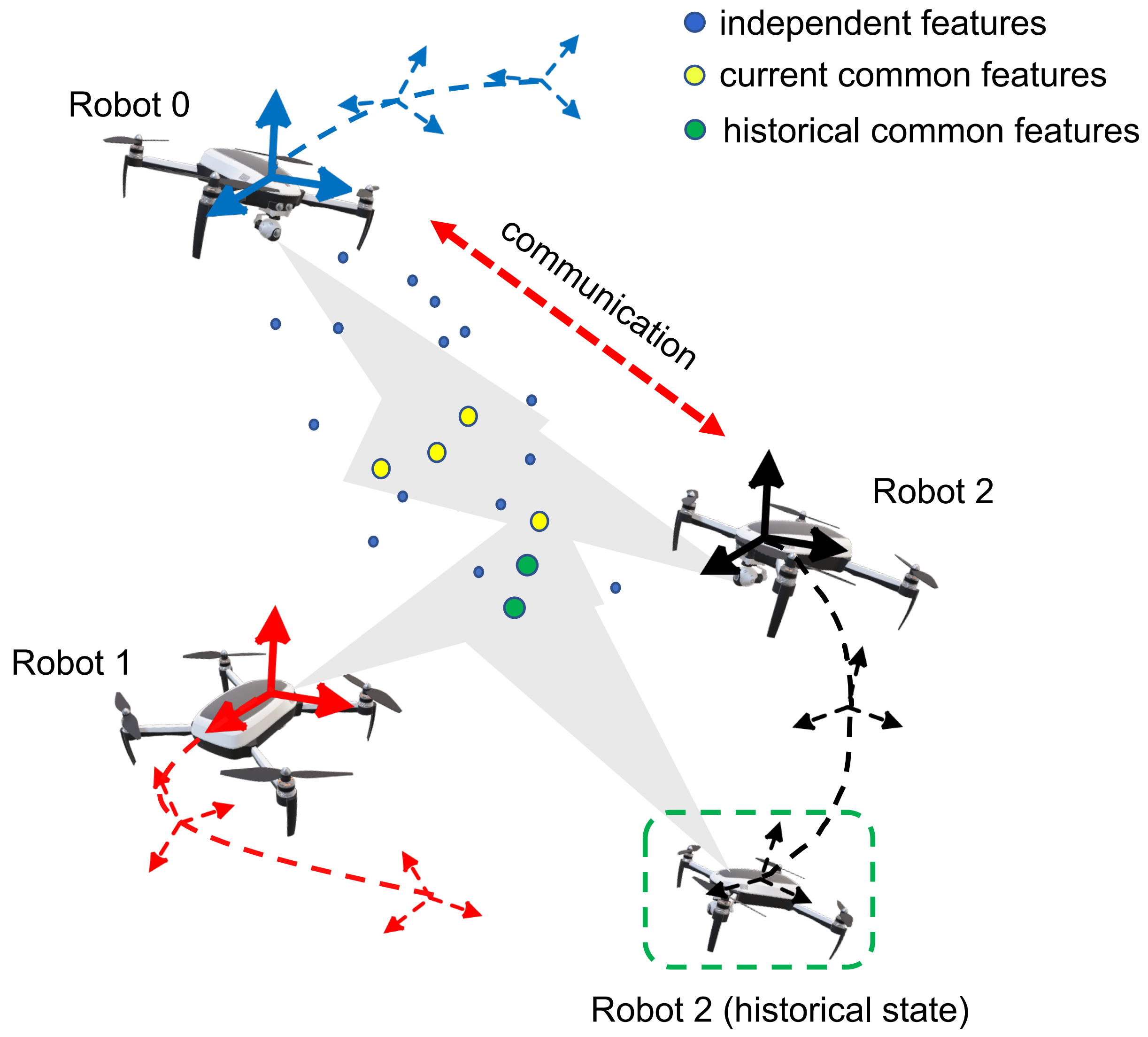
Augmented-Reality Experiences
(credit Apple ARKit)

Problem Formulation - Overview

- Multiple robots are exploring an environment:
  - Robots, when in communication range, can send feature information, current, and historical states
  - Each robot tracks a short “sliding window” of clones
  - Other robot’s states are related through common feature observations

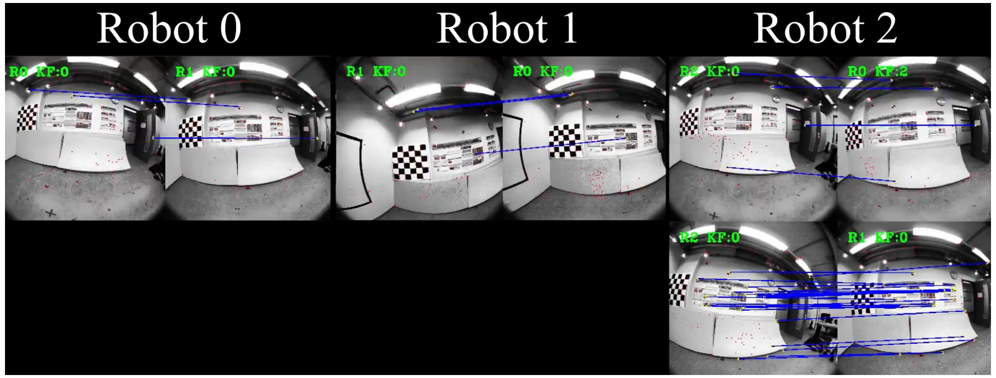
- Different features can be observed:
  - Independent: Only one robot sees these features
  - Current common: Seen from multiple robots that only constrain their current “sliding window”
  - Historical common: The feature seen by one robot currently was seen by another robot before, but not currently.

- **<u>Proposed:</u>** Use common feature constraints to improve the localization accuracy and limit the long-term navigation drift



Experiments

- Estimator was built on top of OpenVINS [Geneva 2020]
- Common features improved trajectory **accuracy** over independent robot state estimation
- The accuracy of **Distributed** estimators is competitive with centralized estimations at a **fraction of computational cost**
- Historical matching is **crucial** to ensure constraints during realistic scenarios:
  - 27% frames matched to other robots' **most recent frames**
  - 42% frames have matched if using **historical**



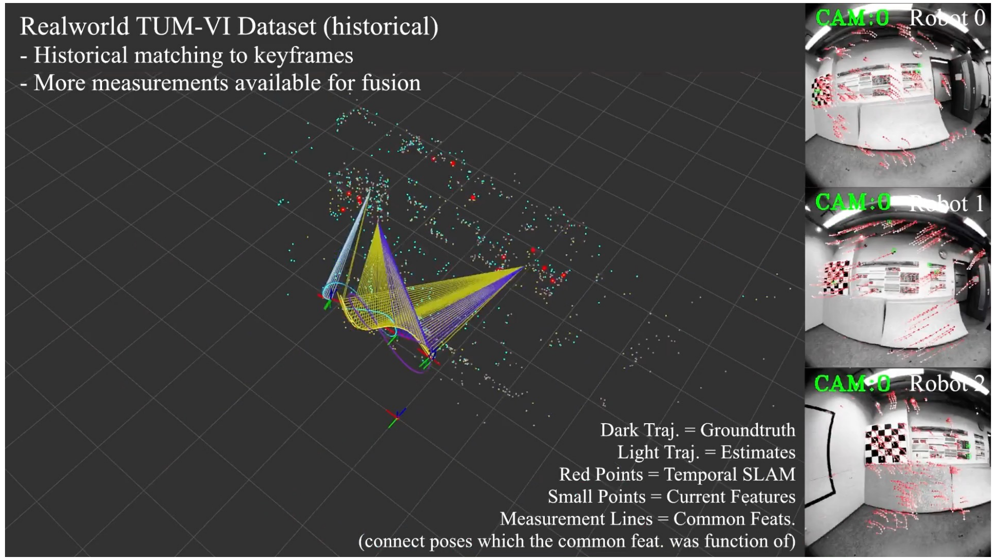


Table 1: Relative pose error (RPE) on TUM-VI datasets in degrees / meters averaged over all robots for the dataset.

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**

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

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