Collaborative SLAM for Facilitating Radiological Search and Mapping with UWB Enabled Multi-Agent Platforms

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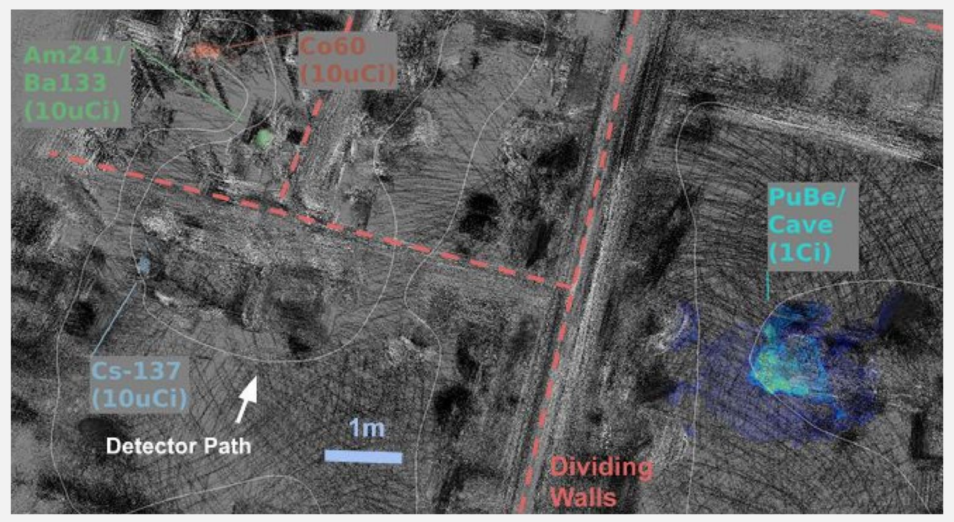
Poster #2

Motivation

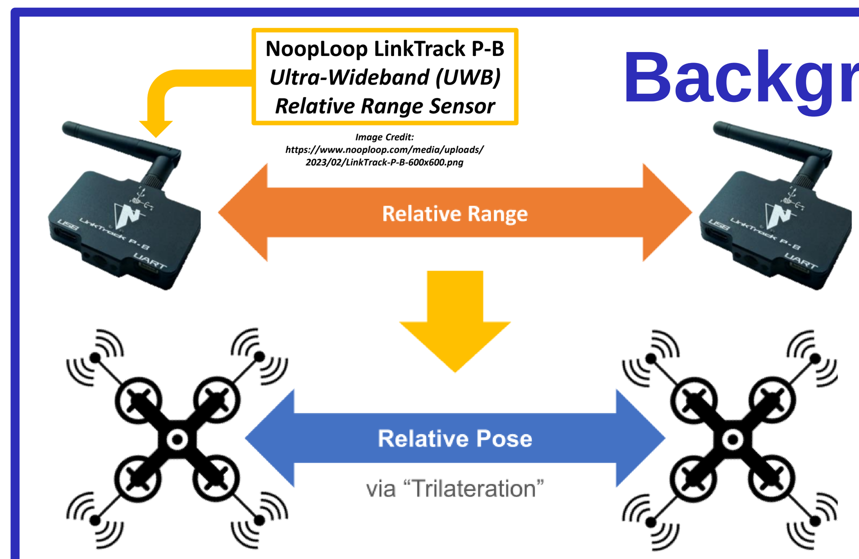
We want to improve radiological search by expanding the capabilities of collaborative SLAM (simultaneous localization and mapping) – i.e., the process where teams of robots make maps of unknown environments. Expanding collaborative SLAM capabilities enables faster/more versatile search and a reduced cost of onboard sensors, allowing the fielding of more agents. Our solution should address these challenges:

(1) GPS denied / No prior maps (2) Low communication bandwidth (3) Dynamic network topology



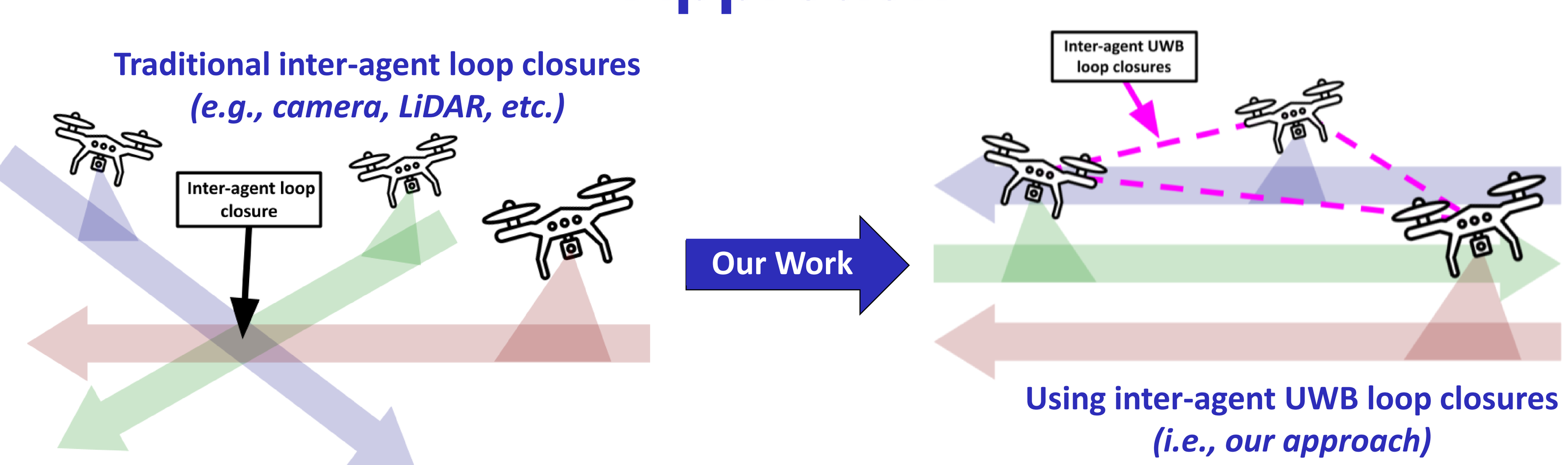
Takeaway: Picture above is the LAMP (Localization and Mapping Platform) and a radiological search map it created. These state-of-the-art results were produced by our collaborators at LBL [1]. Expanding this technology to multiple collaborating LAMP agents would improve radiological search capabilities.

Background



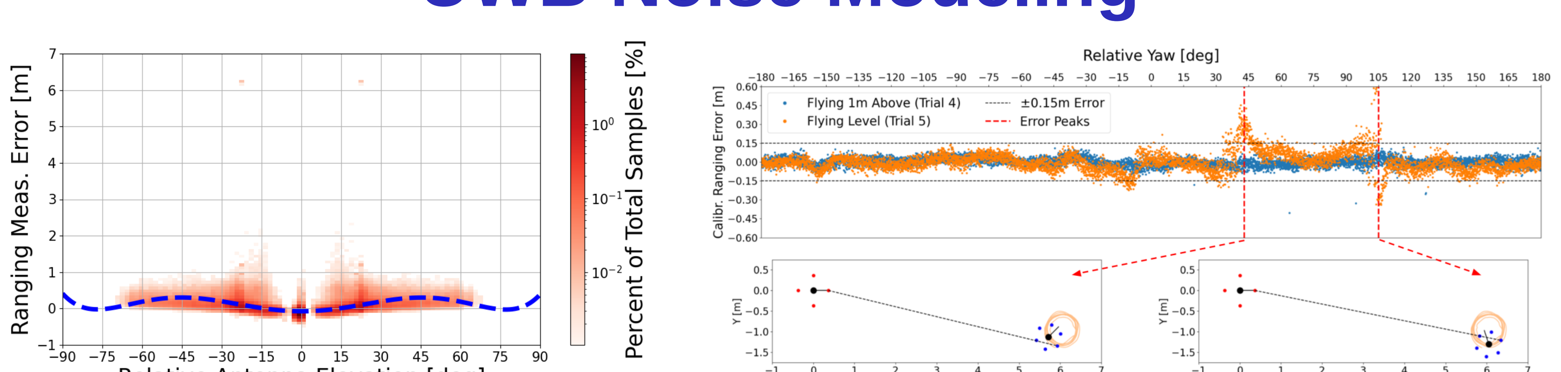
Takeaway: Ultra-Wideband (UWB) is a cheap and mature RF technology that can provide accurate relative range measurements at a high rate without external infrastructure. By equipping each agent with multiple UWB sensors, we can fuse sets of relative range measurements, into a full relative pose estimate (i.e., both relative position and heading). This trilateration process works similarly to GPS.

Approach



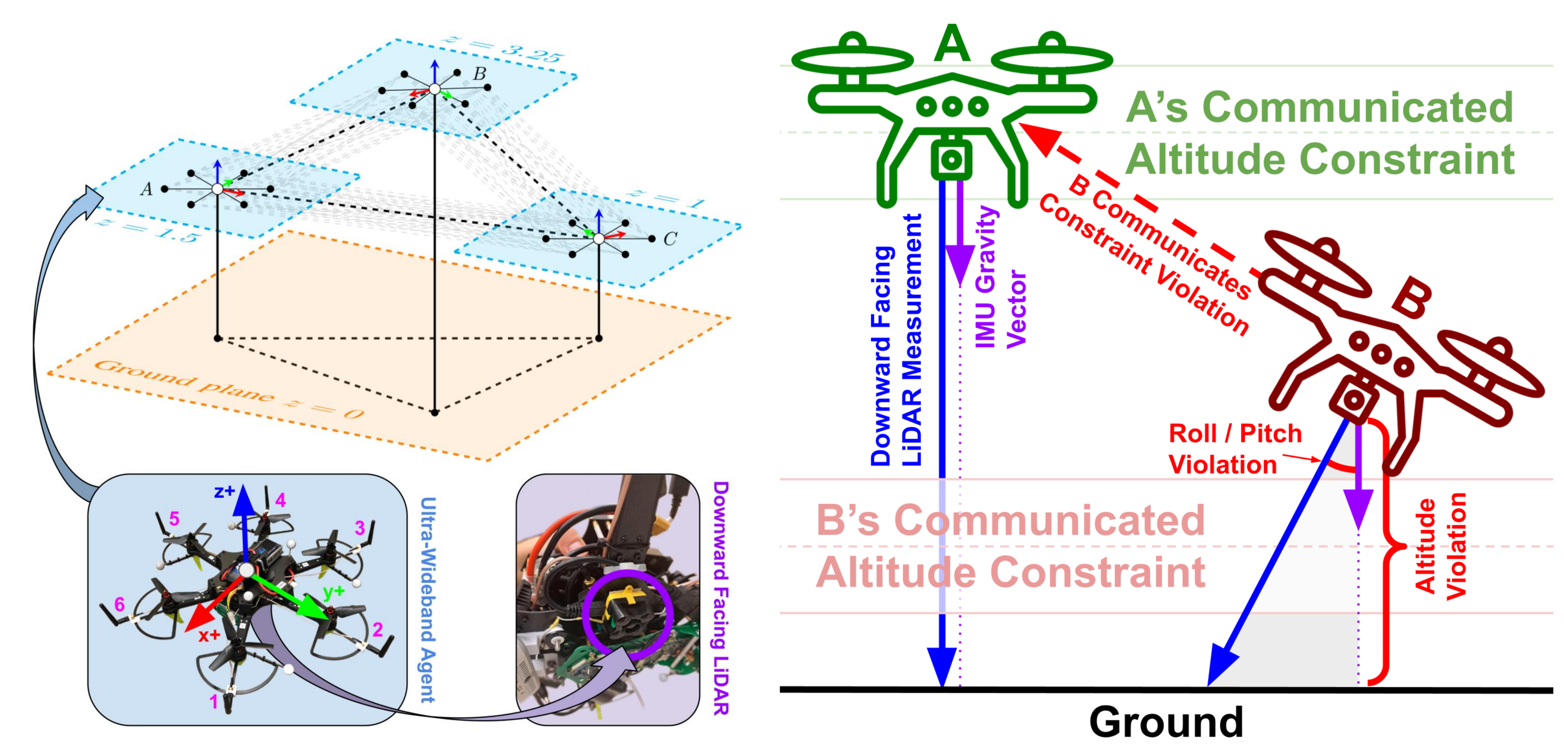
Takeaway: Leveraging inexpensive UWB technology, collaborating agents do not need to cross paths while creating an inter-agent map. This increases the overall speed and effectiveness of radiological search.

UWB Noise Modeling



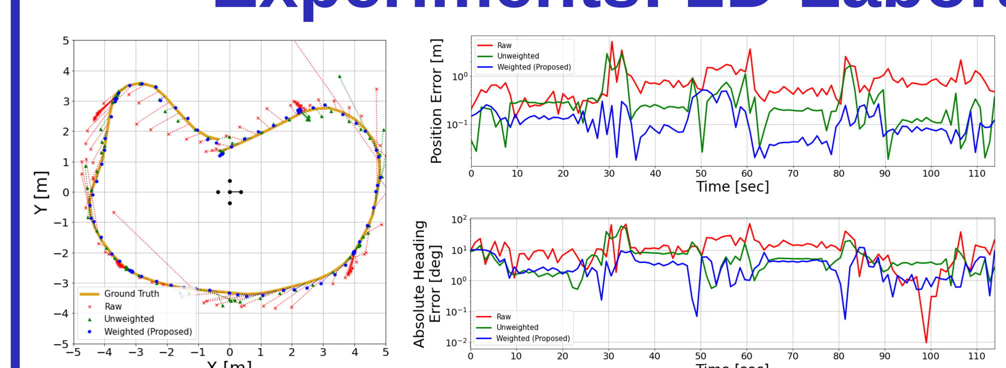
Takeaway: Roboticists often model UWB relative range error as a zero-mean Gaussian and supplement with continuously transmitted measurements, such as odometry. By modeling range measurement error with respect to relative pose (e.g., relative elevation) and obstruction (e.g., the agent's body eclipsing the direct antenna path), our work can achieve similar results *without continuous communication*.

Algorithmic Approach



Takeaway: Our minimal communication protocol enables accurate relative pose estimation *without the need for continuously transmitted measurements*, such as odometry. Our approach only uses *locally* collected UWB relative range measurements and assumptions about each agents' global altitude/roll/pitch. Said assumptions are transmitted *once* and are *locally* monitored by each agent. If an assumption changes or is violated, the agent can perform a *one-off* transmission to notify the swarm.

Experiments: 2D Laboratory Results



Position Error [m]	Scenario					
	kidney-bean			box		
Method	Mean	Max	Std	Mean	Max	Std
Raw	0.76	5.20	0.68	0.93	4.99	0.70
Shift only	0.47	4.77	0.73	0.44	4.61	0.69
MovingAvg only	0.68	3.40	0.47	0.91	3.57	0.59
Unweighted (Eq. 3)	0.36	2.91	0.44	0.45	3.29	0.54
Weighted (Eq. 8) **[Proposed]**	**0.13**	**0.52**	**0.11**	**0.21**	**0.96**	**0.17**

Abs Heading Error [deg]	Scenario					
	kidney-bean			box		
Method	Mean	Max	Std	Mean	Max	Std
Raw	12.06	70.33	12.17	12.11	65.86	10.15
Shift only	8.10	80.20	12.72	6.34	64.33	9.76
MovingAvg only	10.32	57.96	8.73	11.55	50.65	9.01
Unweighted (Eq. 3)	6.15	58.70	8.38	5.99	51.71	7.91
Weighted (Eq. 8) **[Proposed]**	**3.95**	**11.97**	**2.98**	**4.22**	**13.31**	**3.03**

Takeaway: Experiments of 2D approach provides mean abs position and heading errors of 0.21m and 4.22◦ respectively across numerous tests (one trial shown).

Experiments: 3D Laboratory Results

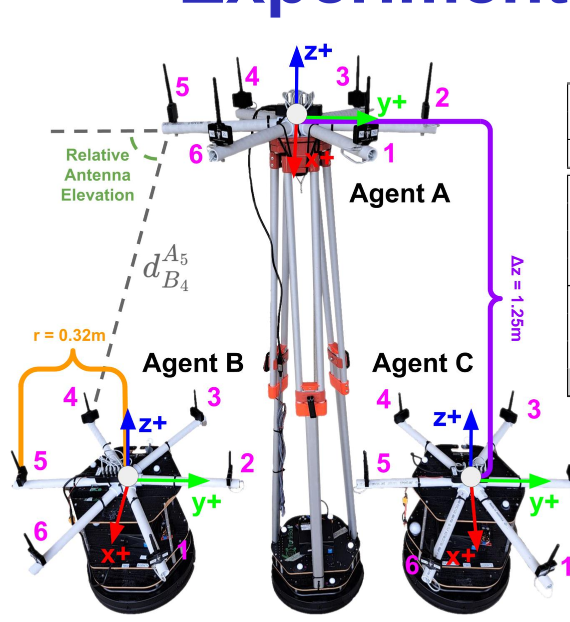
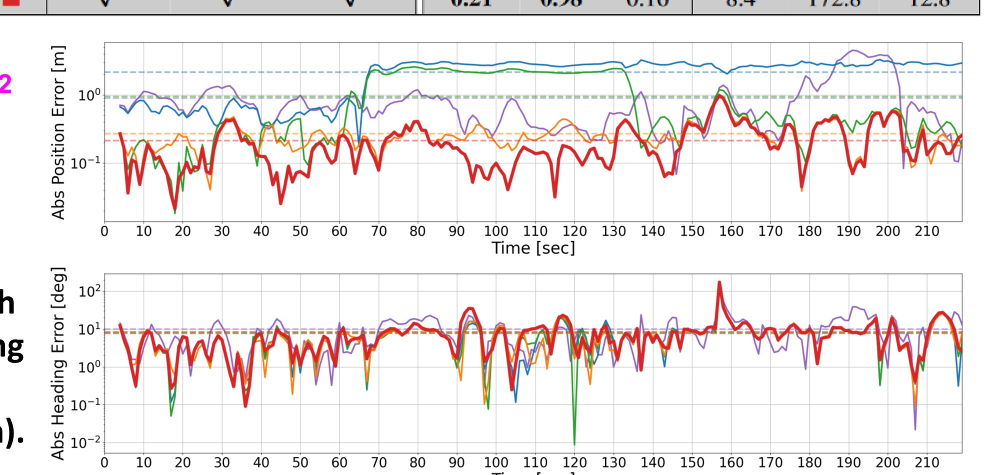


TABLE I: Evaluation of pose error in meters and degrees between algorithms. The final row (red) represents the proposed approach.

Abs Pose Error				Error Component					
				Abs Position Error [m]			Abs Heading Error [deg]		
color	el_bias	z_fixed	Huber	Mean	Max	Std	Mean	Max	Std
purple				0.89	4.50	0.88	10.0	139.9	12.2
	✓			0.89	4.46	0.97	10.0	139.9	**12.1**
		✓		0.42	1.50	0.28	10.1	139.9	**12.1**
	✓	✓		0.34	1.49	0.32	10.4	**139.0**	12.2
blue			✓	2.15	3.29	1.03	7.7	177.7	12.8
green	✓		✓	0.95	2.58	0.90	7.8	177.3	12.8
orange		✓	✓	0.27	1.02	**0.14**	**7.6**	172.6	12.5
red	✓	✓	✓	**0.21**	**0.98**	0.16	8.4	172.8	12.8



Takeaway: Experiments of 3D approach provides mean abs position and heading errors of 0.24m and 9.5◦ respectively across numerous tests (one trial shown).

References

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- [3] Xu, Hao, et al. "Omni-swarm: A Decentralized Omnidirectional Visual-Inertial-UWB State Estimation System for Aerial Swarm." arXiv preprint arXiv:2103.04131 (2021).
- [4] Xu, Hao, et al. "Decentralized visual-inertial-UWB fusion for relative state estimation of aerial swarm." 2020 IEEE International Conference on Robotics and Automation (ICRA). IEEE, 2020.
- [5] Torgesen, Andrew J. Autonomous Sensing and Navigation in Challenging Environments Using Unmanned Air Vehicles in Single and Multi-Agent Settings. Diss. Massachusetts Institute of Technology, 2021.
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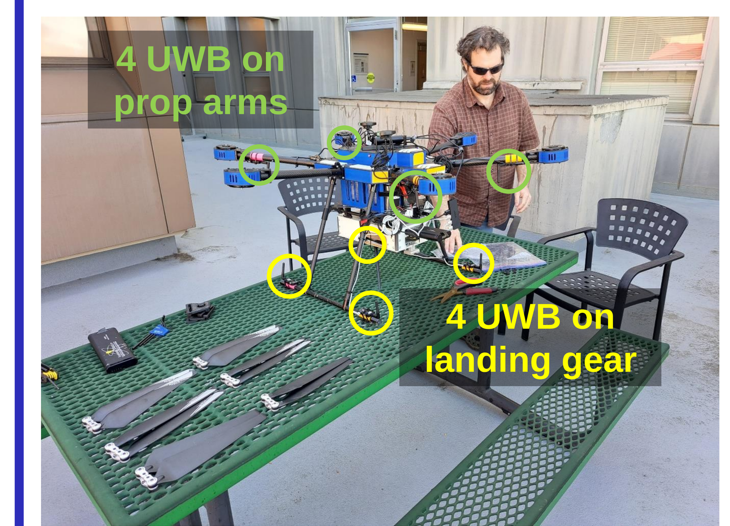
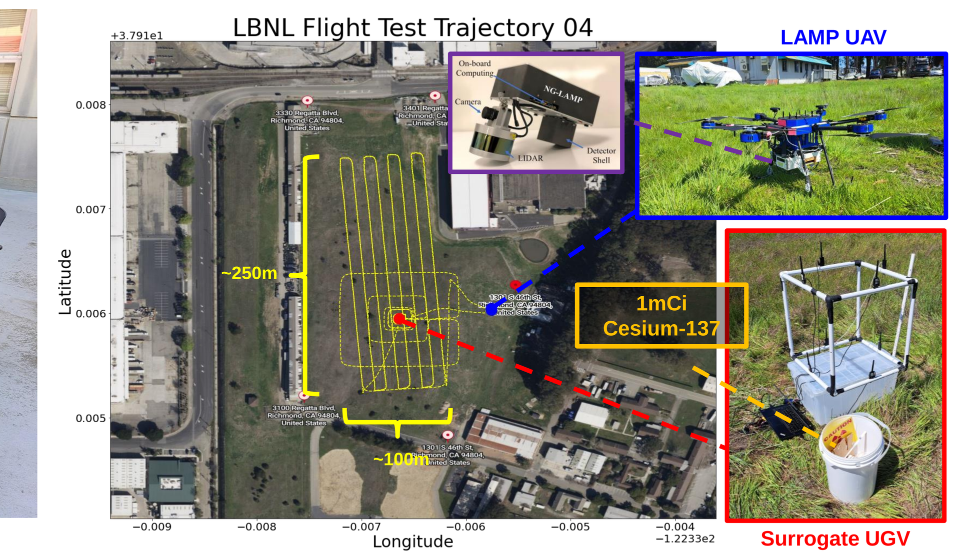
Experiments: LBL Flight Tests





Takeaway: Initial experiments equip LAMP UAV with multiple UWB sensors for real-time relative pose estimation. Future work will fly multiple LAMPs and integrate UWB directly into SLAM solution.

Mathematical Formulation

$$\min_{\substack{x_B^A, y_B^A \in \mathbb{R} \\ \gamma_B^A \in [-180^\circ, 180^\circ]}} \sum_{i=1}^{N_A} \sum_{j=1}^{N_B} \ell\left(e_{B_j}^{A_i}\left(\mathbf{T}(\underbrace{x_B^A, y_B^A}_{\text{free}}, \underbrace{\hat{z}_B^A, \hat{\alpha}_B^A, \hat{\beta}_B^A}_{\text{constrained}}, \underbrace{\gamma_B^A}_{\text{free}}) \right) \right)$$

$$e_{B_j}^{A_i}(\mathbf{T}_B^A) \triangleq \underbrace{\left(\tilde{d}_{B_j}^{A_i} - \bar{d}_{B_j}^{A_i}(\mathbf{T}_B^A) \right)}_{\text{bias adjusted measurement}} - \underbrace{d_{B_j}^{A_i}(\mathbf{T}_B^A)}_{\text{expected measurement}}$$

Takeaway: We formulate our approach as a nonlinear optimization problem (i.e., trilateration). By leveraging our minimal communication model (see Algorithmic Approach), a robust loss function (Huber loss), and a learned pose-dependent measurement bias correction (see UWB Noise Modeling), we can estimate a full 3D pose from a single set of instantaneous relative range measurements (i.e., no supplementary measurements need to be continuously transmitted).

Next Steps

- Integrate 3D pose error model (i.e., DOP) into SLAM pipeline
- Integration of UWB into full Kimera-Multi SLAM stack
- CORA extension, LBL plume exploration, GT collaboration
- Working towards multiple airborne LAMP drones

Publications

Multi-Agent Relative Pose Estimation with UWB and Constrained Communications
Presented at IEEE's IROS'22 Conference in Kyoto Japan.

CORA: Certifiably Correct Range-Aided SLAM
Under review; posted to arXiv February 2023

MURP: Multi-Agent Ultra-Wideband Relative Pose Estimation with Constrained Communications in 3D Environments
Being sent to IEEE's RA-L; Posted to arXiv December 2023

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National Nuclear Security Administration

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