Agriculture Robotics: Large-scale Autonomy and Semantic Mapping with UAVs

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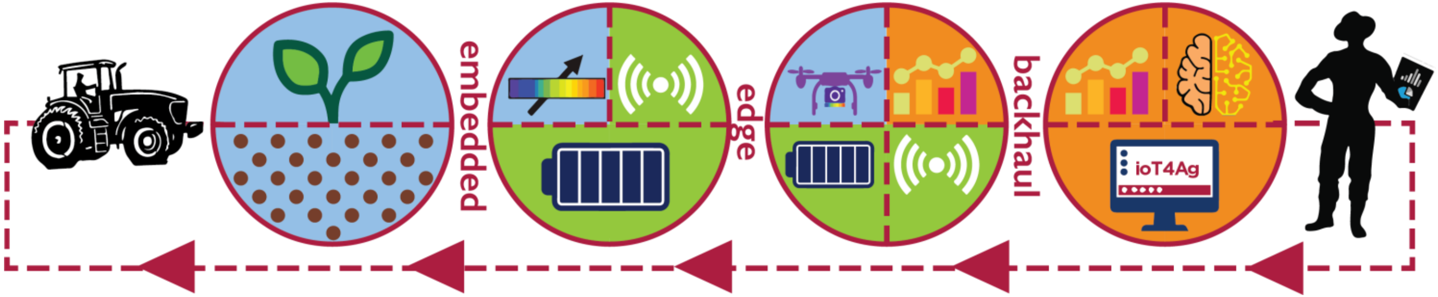
Motivation

Need and Solution

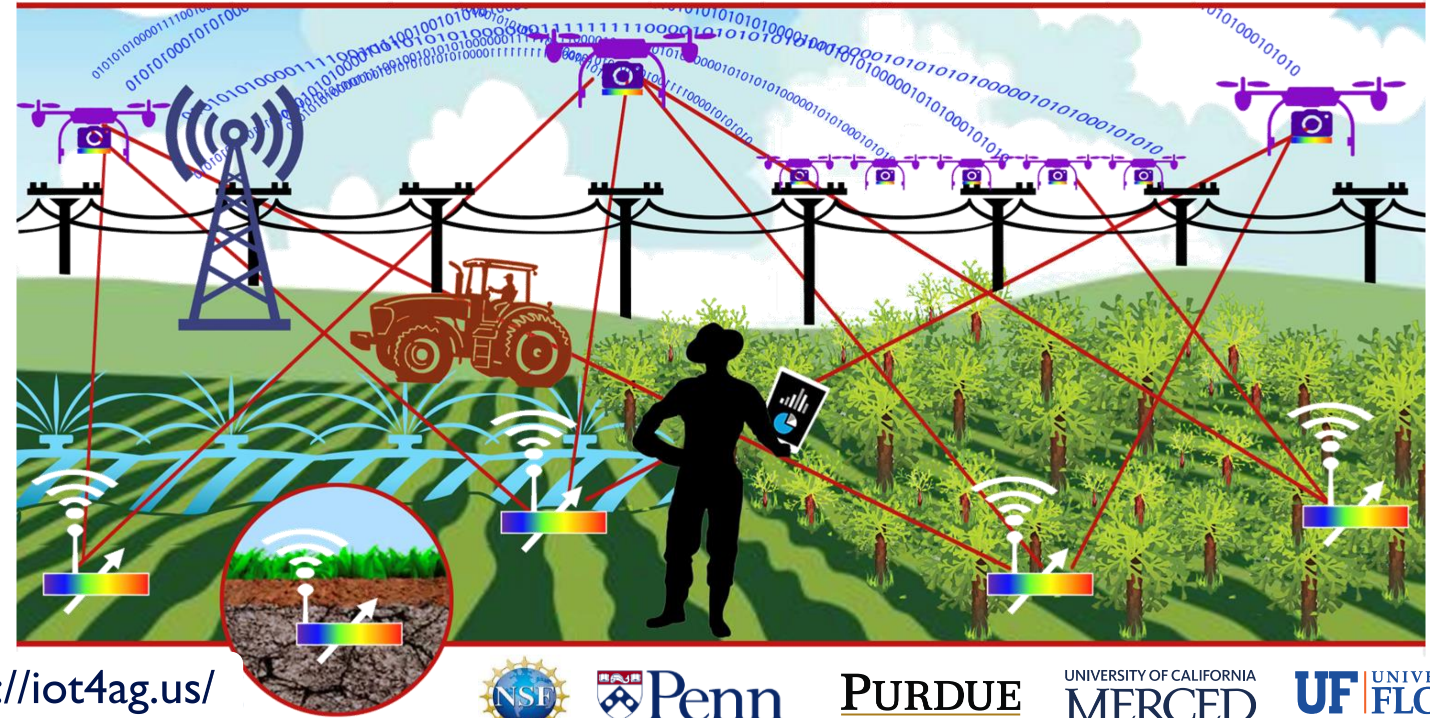
- Worldwide hunger: 1B malnourished, expected to grow to 9B by 2050
- Scarcity of land: 80% of the land that can be cultivated is already in use
- Water shortage: agriculture accounts for over 70% usage of fresh water
- Inefficient farming: pathogens
- Climate change: need to adapt to variations

Can we imagine an integrated system for early detection and intervention to improve outcomes in agricultural crop production?



Center for IoT for Precision Agriculture

To create and translate to practice Internet of Things (IoT) technologies for precision agriculture and to train and educate a diverse workforce that will address the societal grand challenge of food, energy, and water security for decades to come - *Prof. Cherie Kagan, director*

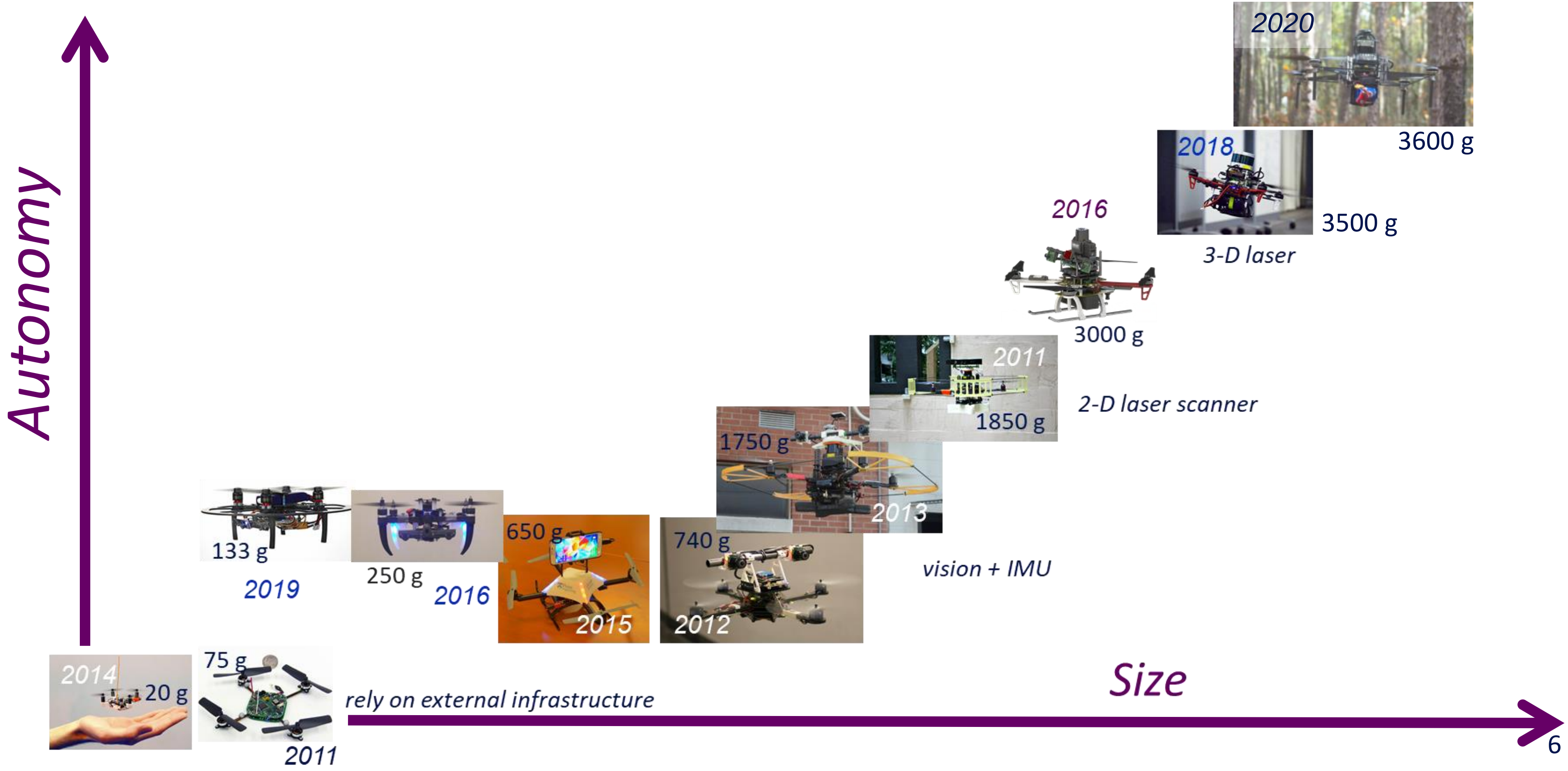


https://iot4ag.us/

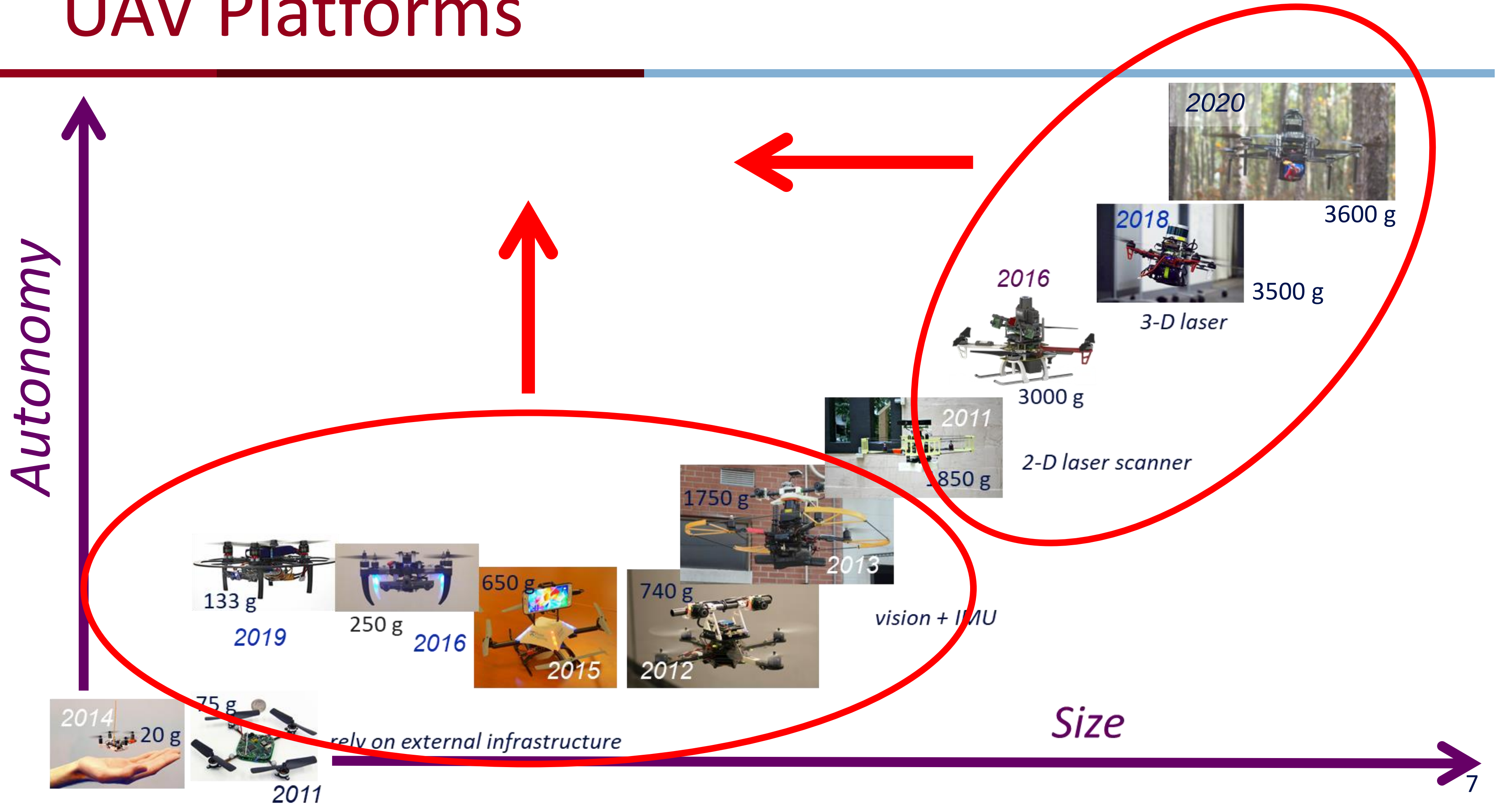
NSF Penn PURDUE UNIVERSITY UNIVERSITY OF CALIFORNIA MERCED UF UNIVERSITY of FLORIDA

Hardware Systems

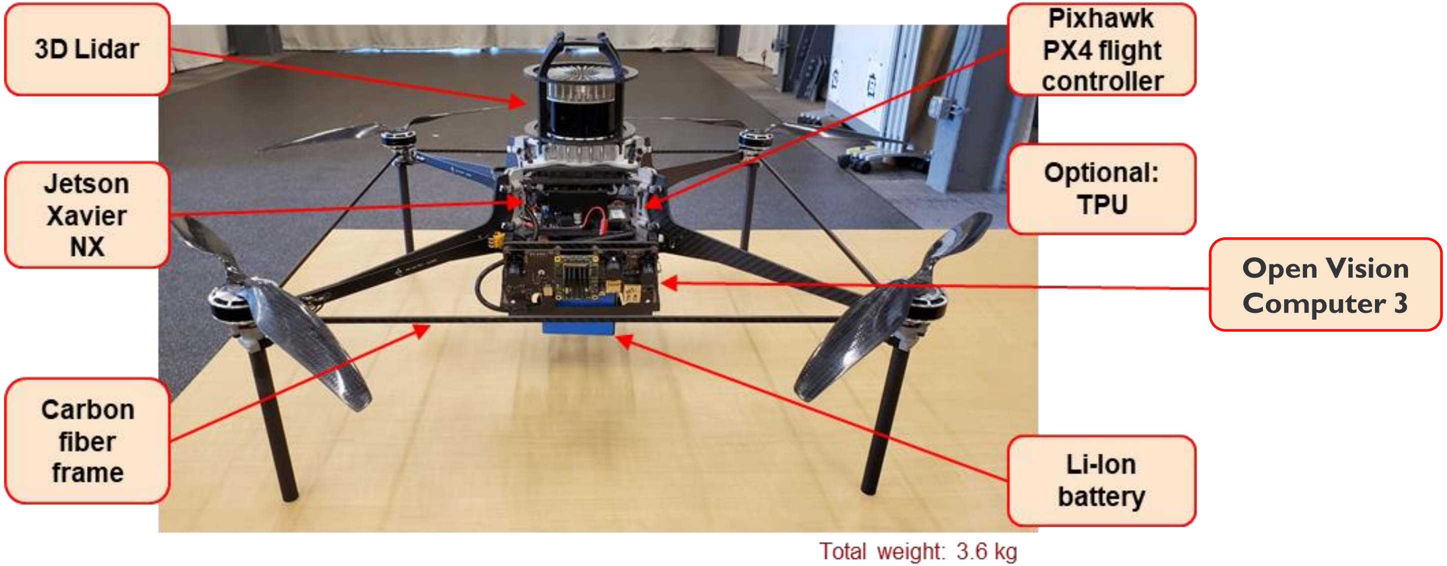
UAV Platforms



UAV Platforms

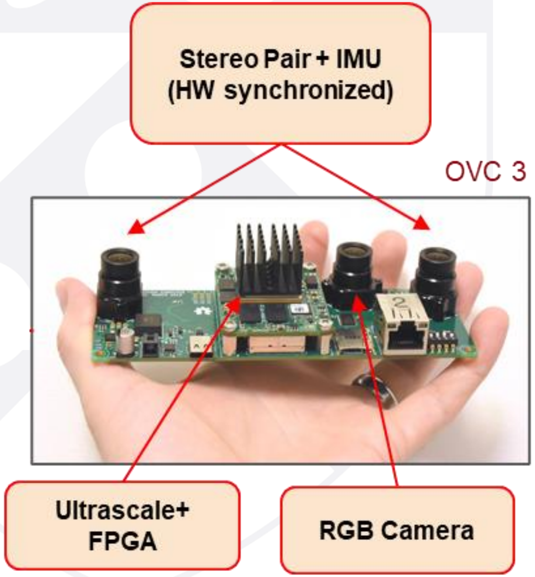


FALCON4 Platform

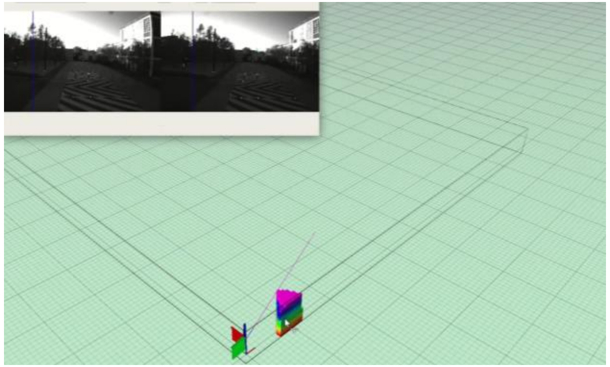


Fully-loaded flight time of ~35 minutes; modular; 1.1m tip-to-tip

Open Vision Computer 3



- 2 grayscale + 1 RGB sensor
- Ultrascale+ MPSoC
- Timestamping on device
- Extensible:
  - 4 stereo camera boards
  - VectorNav VN100 IMU
  - GPIO



Quigley, Morgan, Kartik Mohta, …& Vijay Kumar, Camillo J. Taylor. "The open vision computer: An integrated sensing and compute system for mobile robots." In 2019 International Conference on Robotics and Automation (ICRA), pp. 1834-1840. IEEE, 2019.

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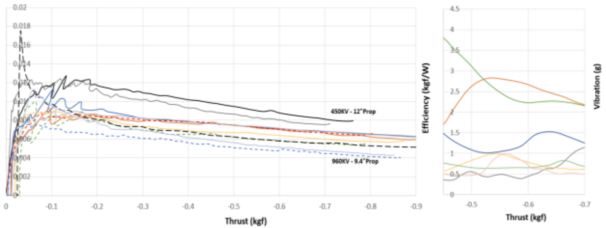
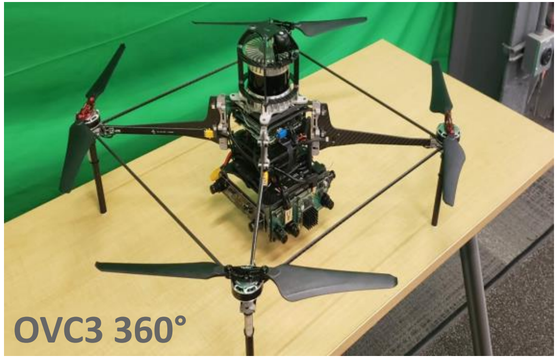
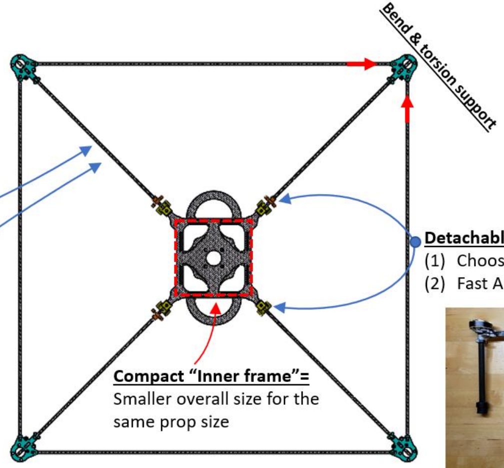
Optimized Electro-mechanical Design



- High efficiency
- Low Vibrations
- Flexible payload
- Flexible compute – NUC / TX2 / Jetson Xavier NX





Low Drag =
(1) Less vibrations
(2) Higher thrust efficiency

1 **Lower Weight for the "same" stiffness**

Fast and Easy Assembly

Flexible (Sensors, Compute, Size….)

Compact "Inner frame"=
Smaller overall size for the same prop size

Detachable Arms =
(1) Choose the length of the arms/props
(2) Fast Arm replace

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Lead designer: A. Cohen

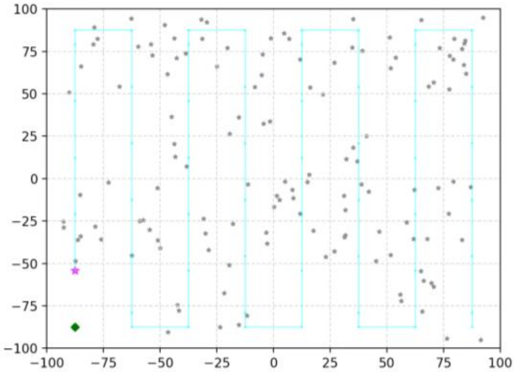
Algorithms and Software Systems

Technical Challenges

Autonomous flight

Detection, classification, and localization

Semantic mapping at scale



Active information gathering

Autonomous Flight System

K. Sun, K. Mohta, B. Pfrommer, M. Watterson, S. Liu, Y. Mulgaonkar, C. J. Taylor, and V. Kumar, "Robust Stereo Visual Inertial Odometry for Fast Autonomous Flight", RAL 2018

Penn Engineering

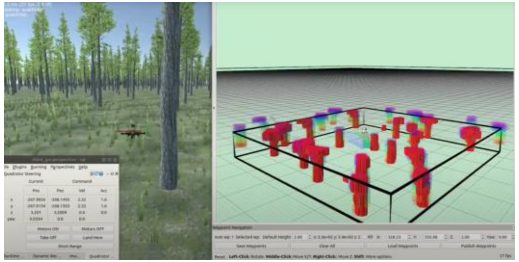
S. Liu, N. Atanasov, K. Mohta, and V. Kumar, "Search-based Motion Planning for Quadrotors using Linear Quadratic Minimum Time Control," IROS 2017.

1 State Estimation (Stereo + IMU)

$$\mathbf{x}_I = \left({}^I_G\mathbf{q}^\top \quad \mathbf{b}_g^\top \quad {}^G\mathbf{v}_I^\top \quad \mathbf{b}_a^\top \quad {}^G\mathbf{p}_I^\top \quad {}^I_C\mathbf{q}^\top \quad {}^I\mathbf{p}_C^\top \right)^\top$$

orientation, gyro bias, velocity, acc bias, position, cam-IMU extrinsics

2 Local map



3 Motion planning

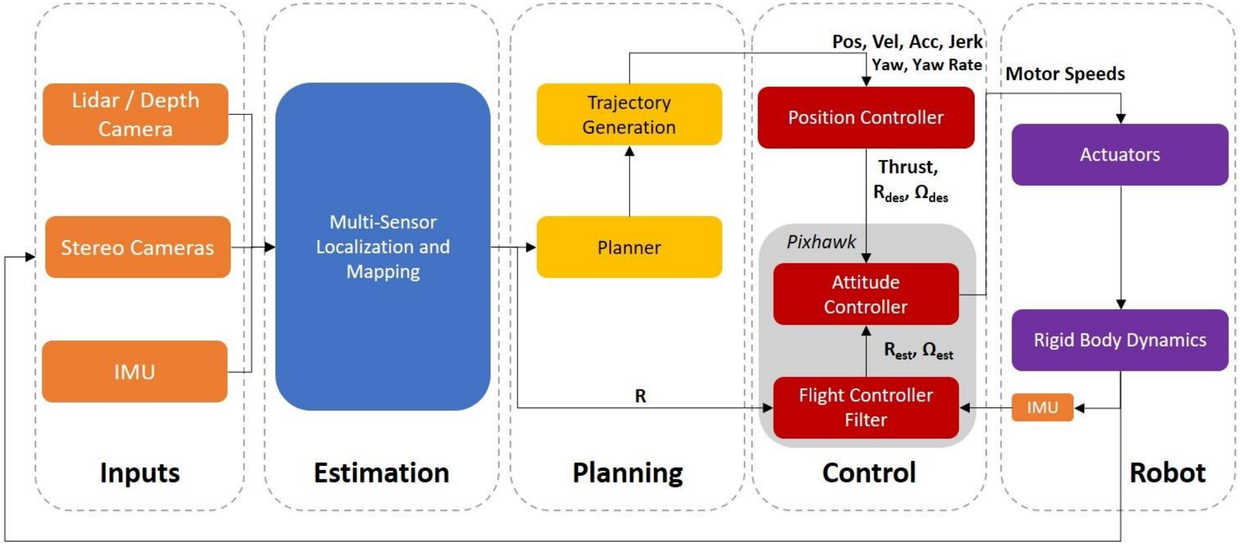
$$\min_{u(t),\, T} J(x(t), u(t)) + \rho T$$

$$\dot{x} = Ax(t) + Bu(t),\ u(t) \in \mathcal{U},\ \forall t \in [0, T]$$

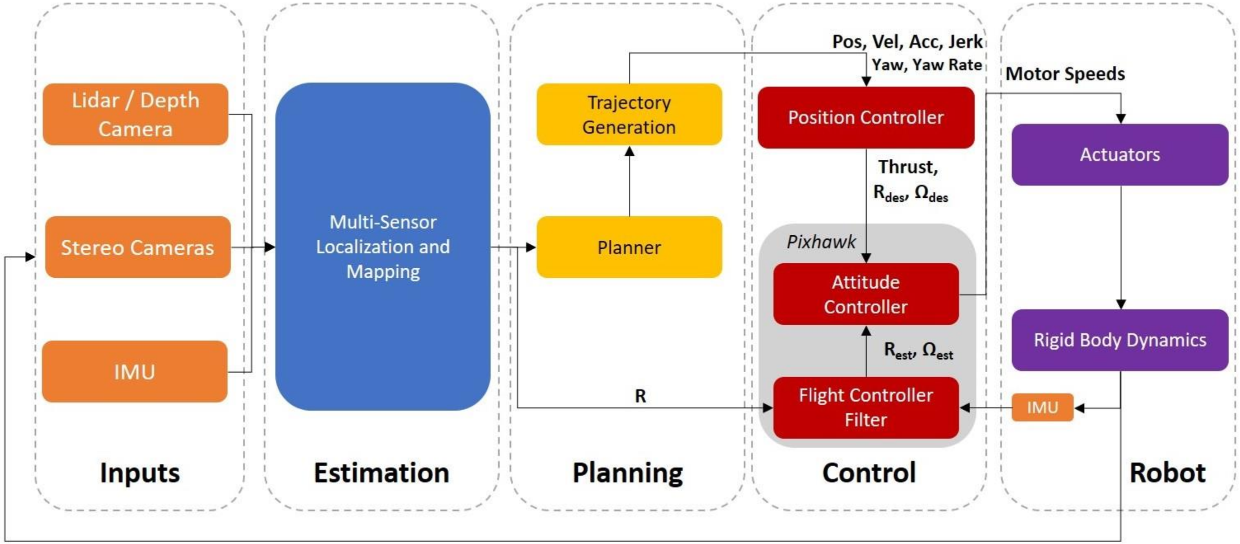
$$x(0) = x_0,\ x(T) \in \mathcal{X}^{\text{goal}},\ x(t) \in \mathcal{X}^{\text{free}}$$

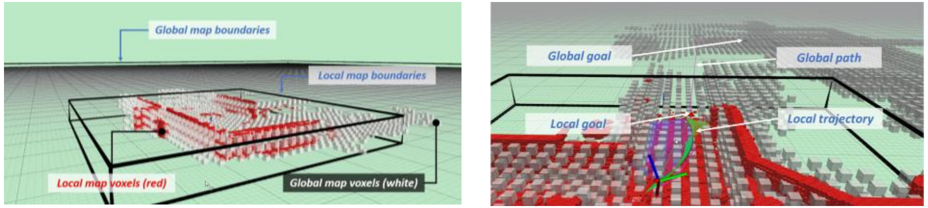
13

Autonomous Flight System



Autonomous Flight System





Local-global mapper and planner

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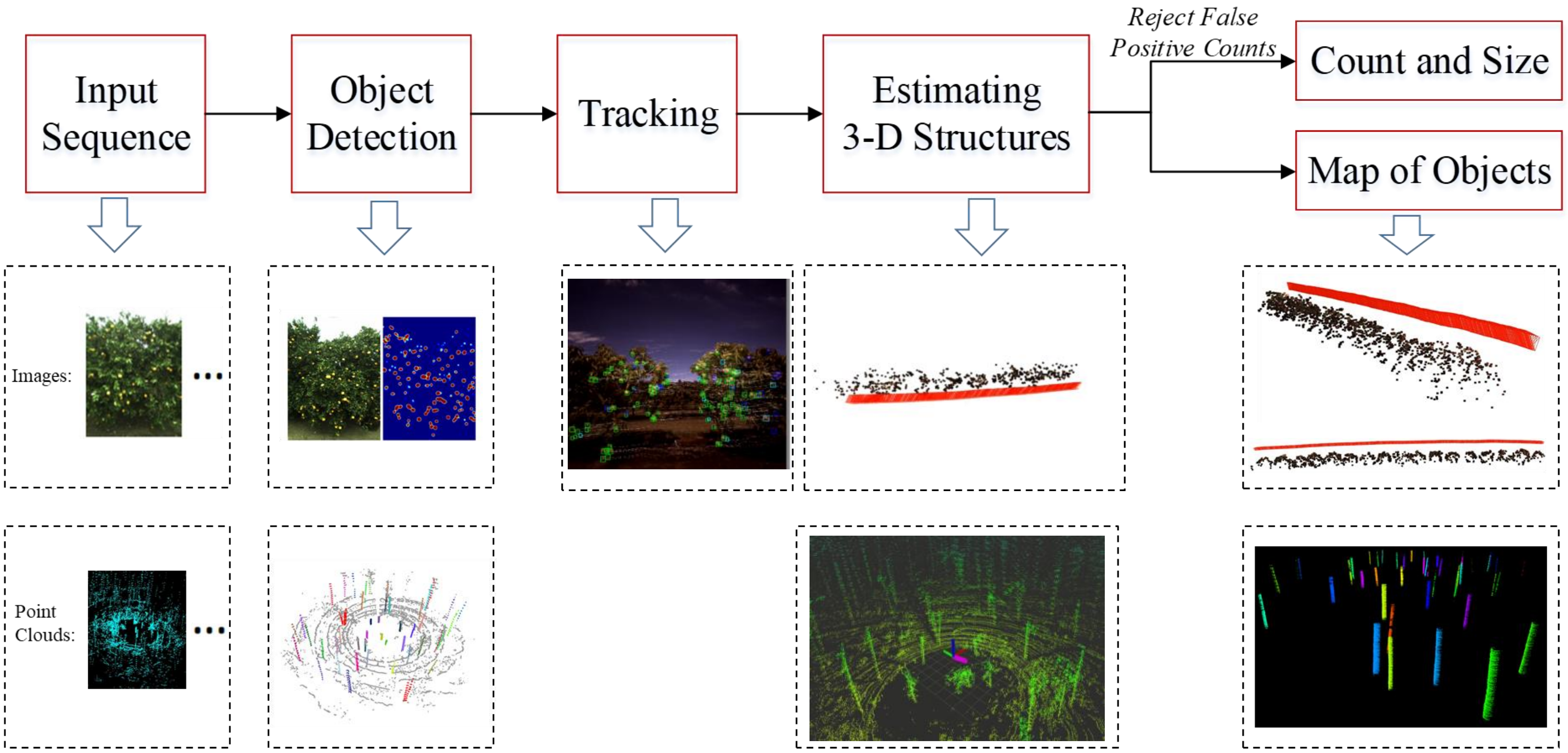
Semantic Mapping System



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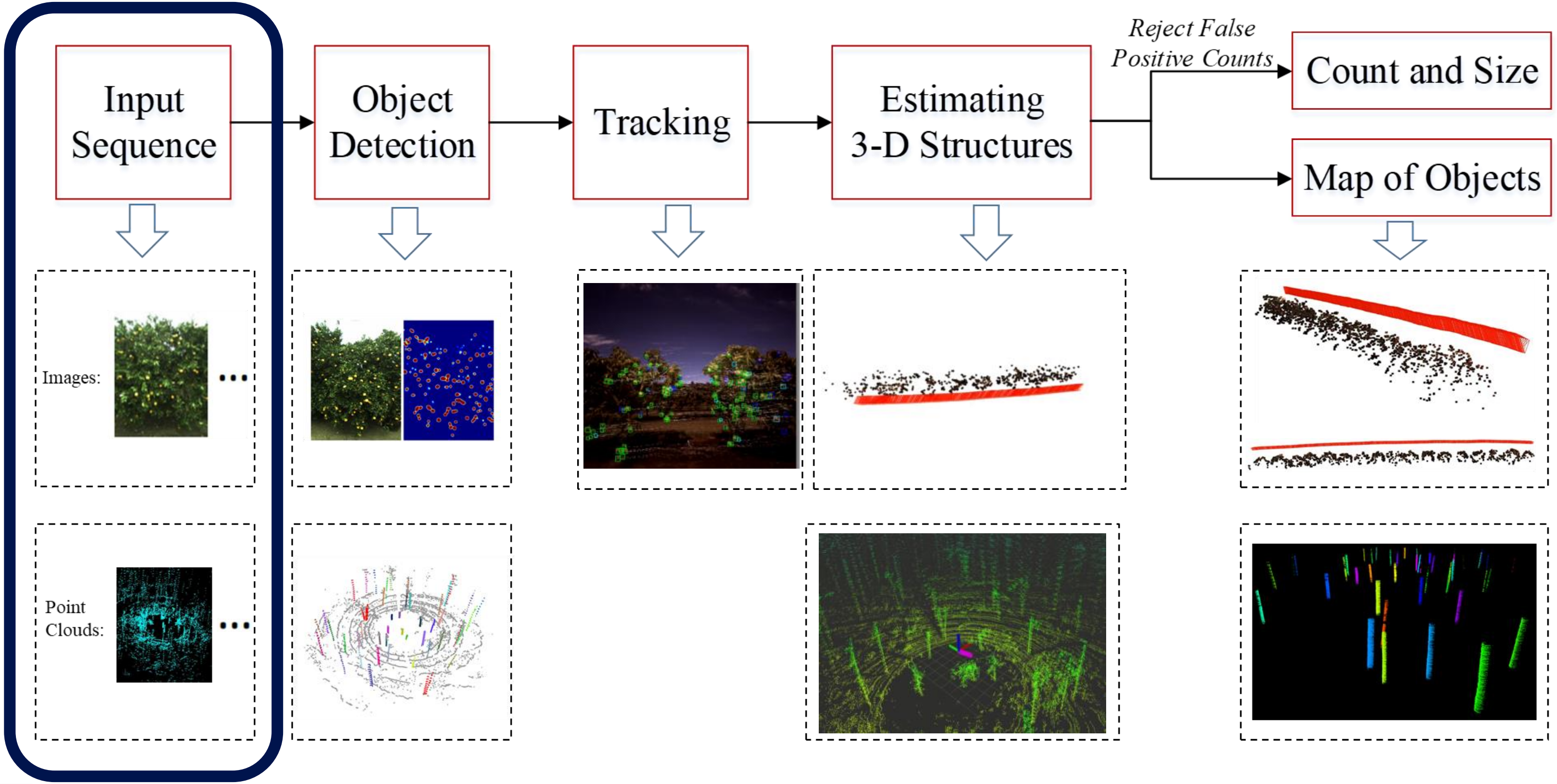
Semantic Mapping System



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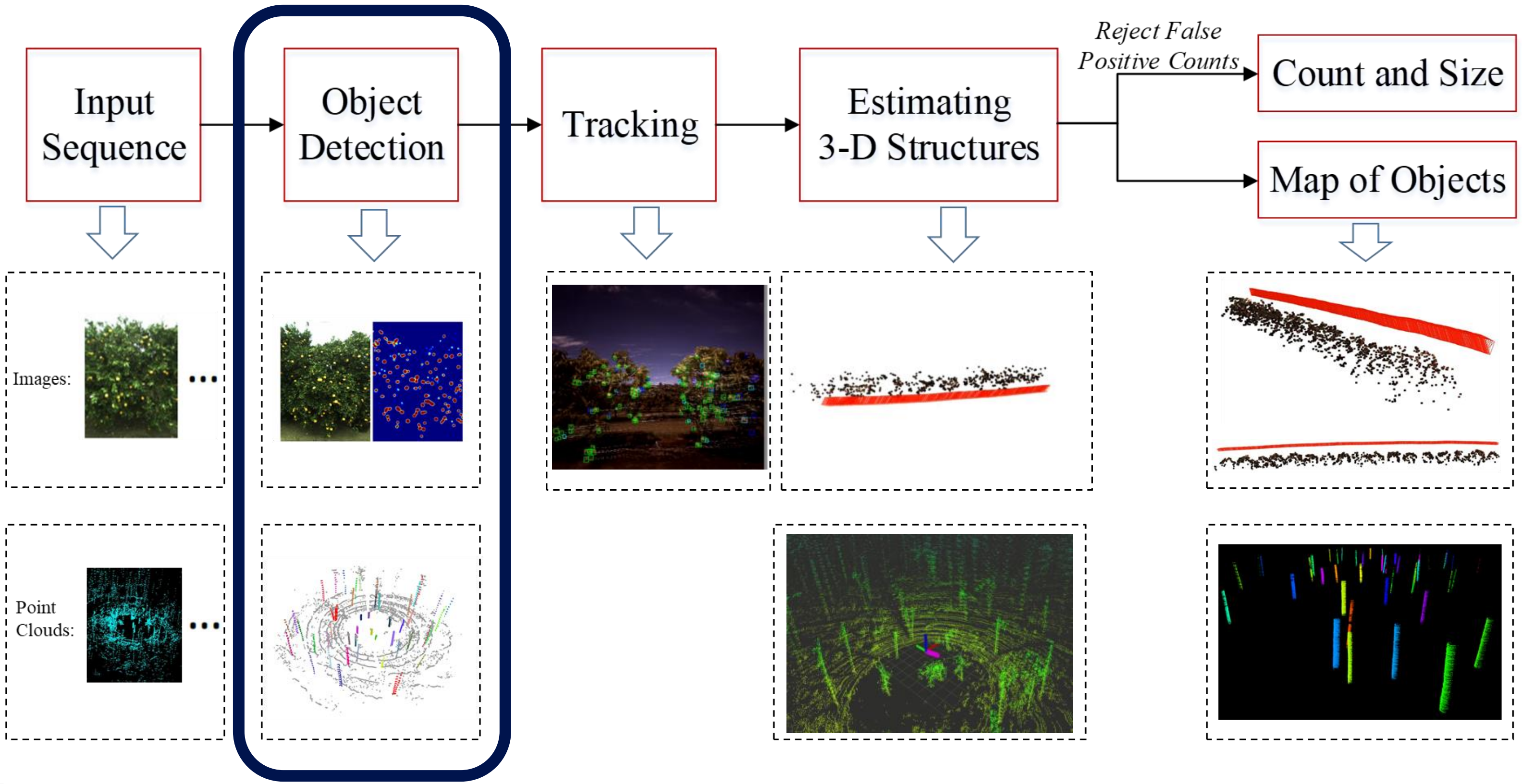

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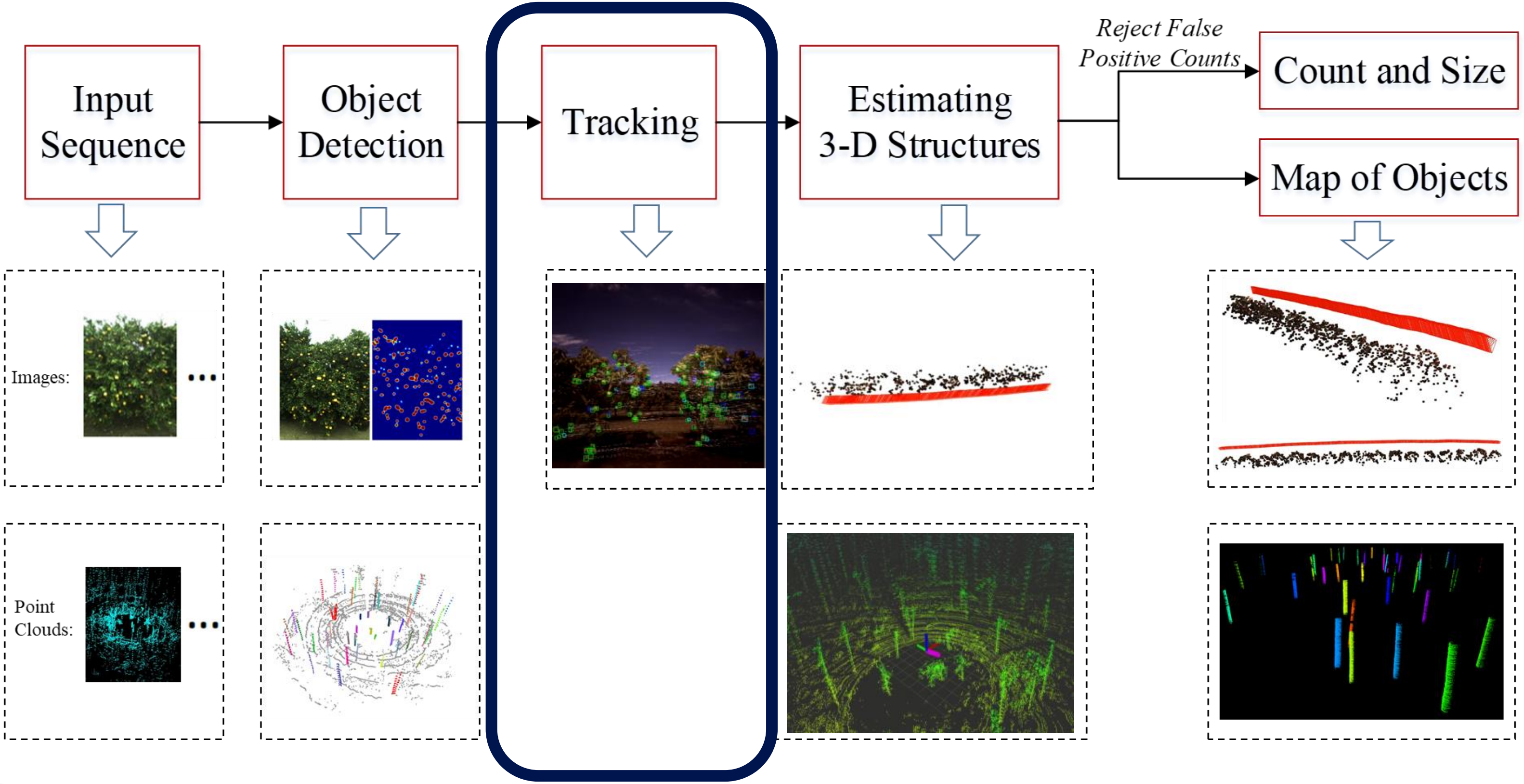

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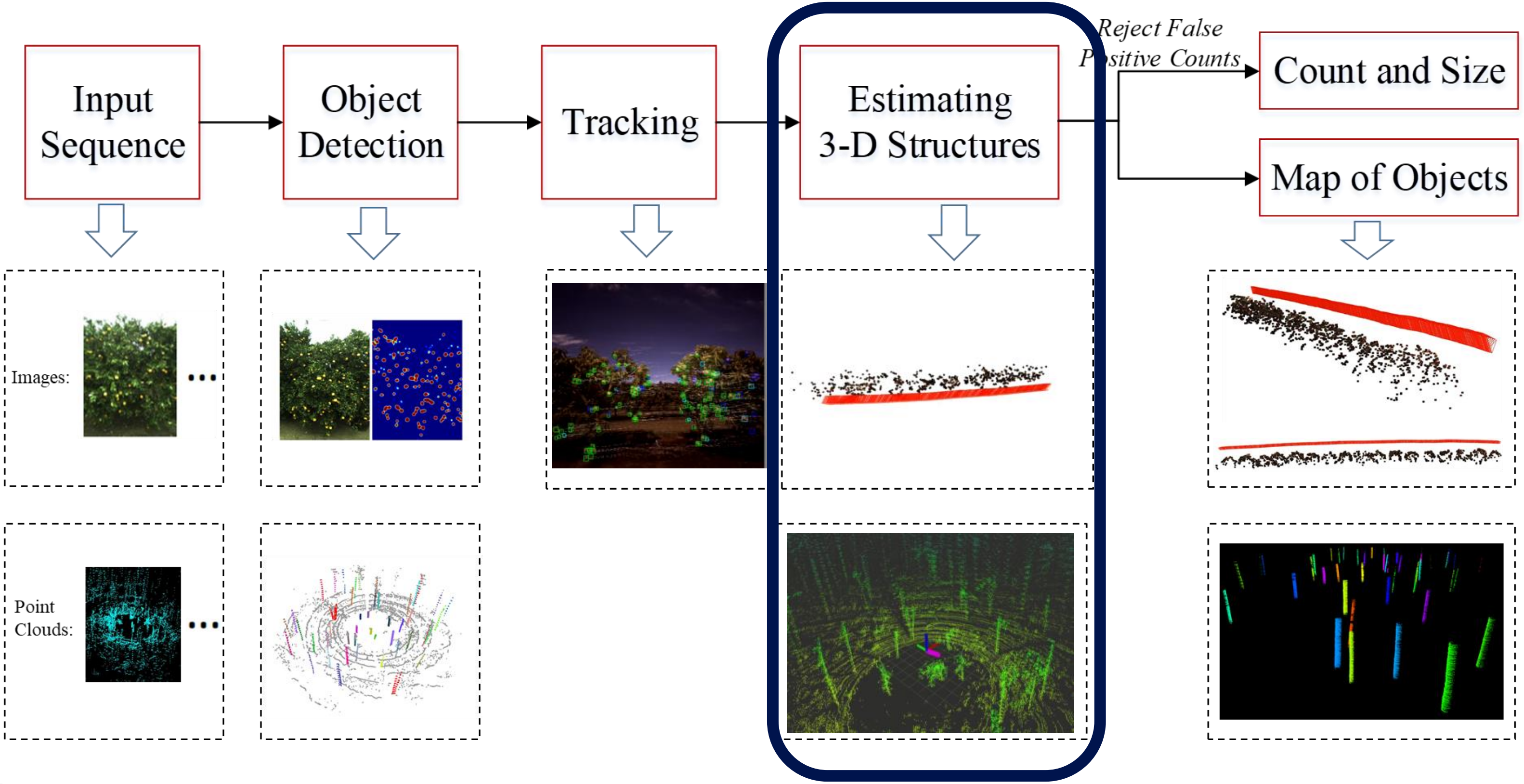

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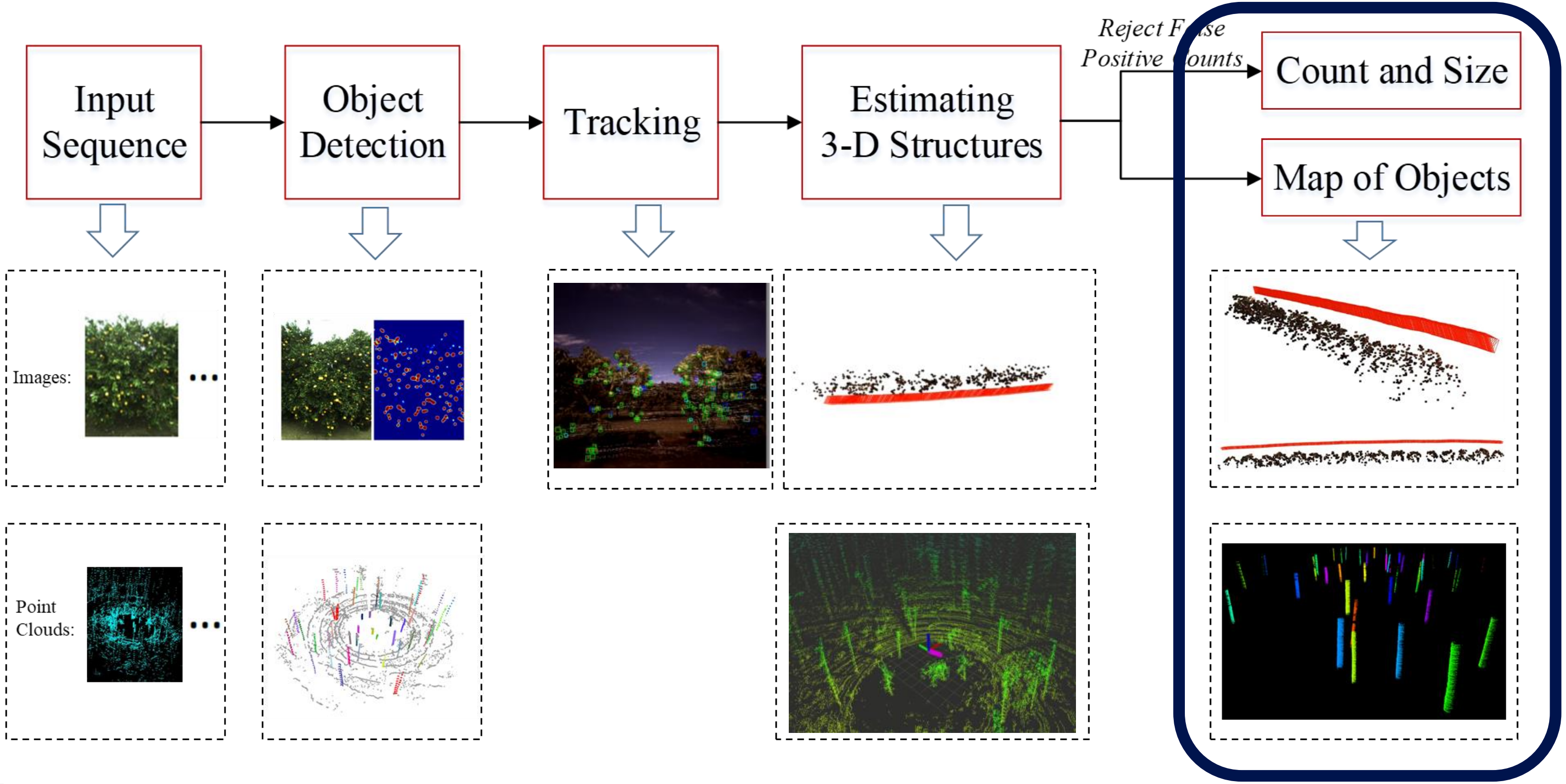

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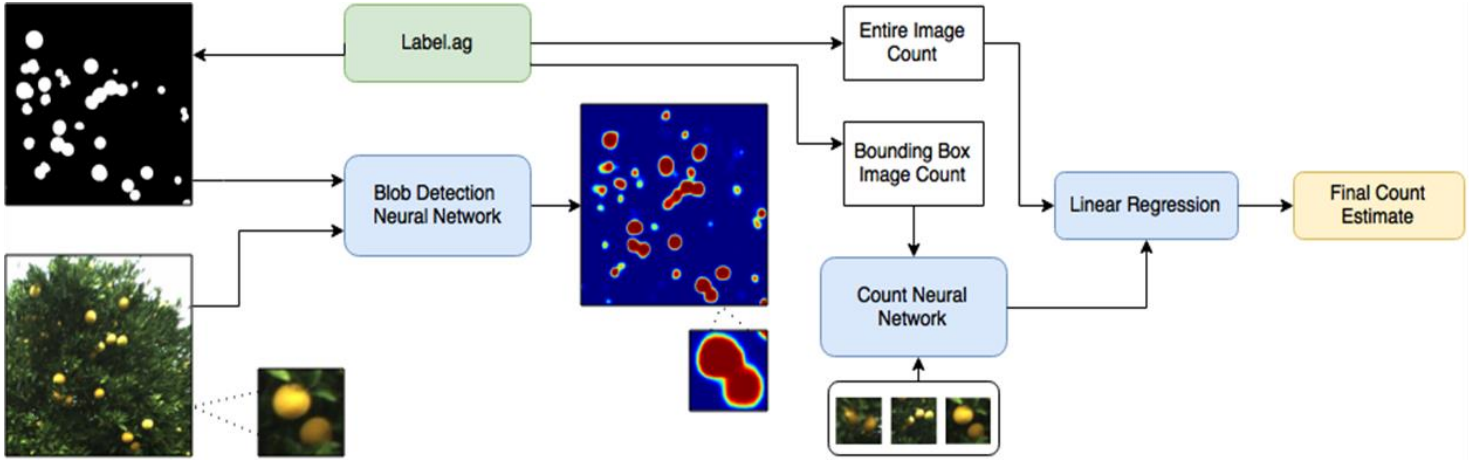
Fruit Counting from Images



Label.ag: a crowd-sourcing labeling platform to rapidly generate labels.	**Blob Detection Neural Network:** a fully convolutional network (FCN) [1] to segment fruit blob regions.	**Count Neural Network:** a convolutional network counts the fruit in each region.	**Linear Regression:** maps individual region counts to total count

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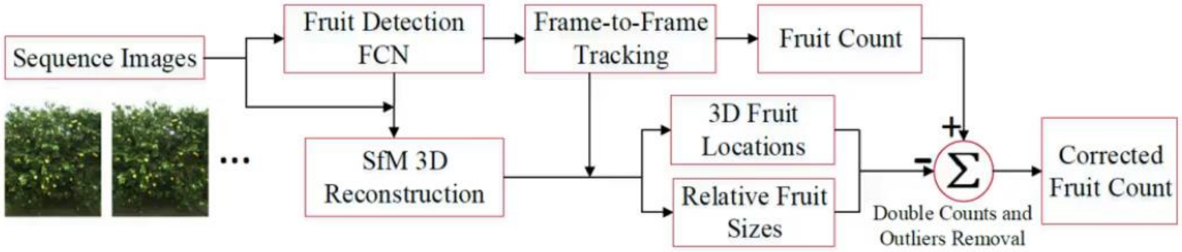
Steven W Chen, Shreyas Skandan, Sandeep DCunha, Jnaneshwar Das, Edidiong Okon, Chao Qu, Camillo Jose Taylor, and Vijay Kumar, Counting Apples and Oranges with Deep Learning: A Data Driven Approach, *IEEE Robotics and Automation Letters*, 2017.

Fruit Mapping from Videos

Robust Fruit Counting: Combining Deep Learning, Tracking, and Structure from Motion



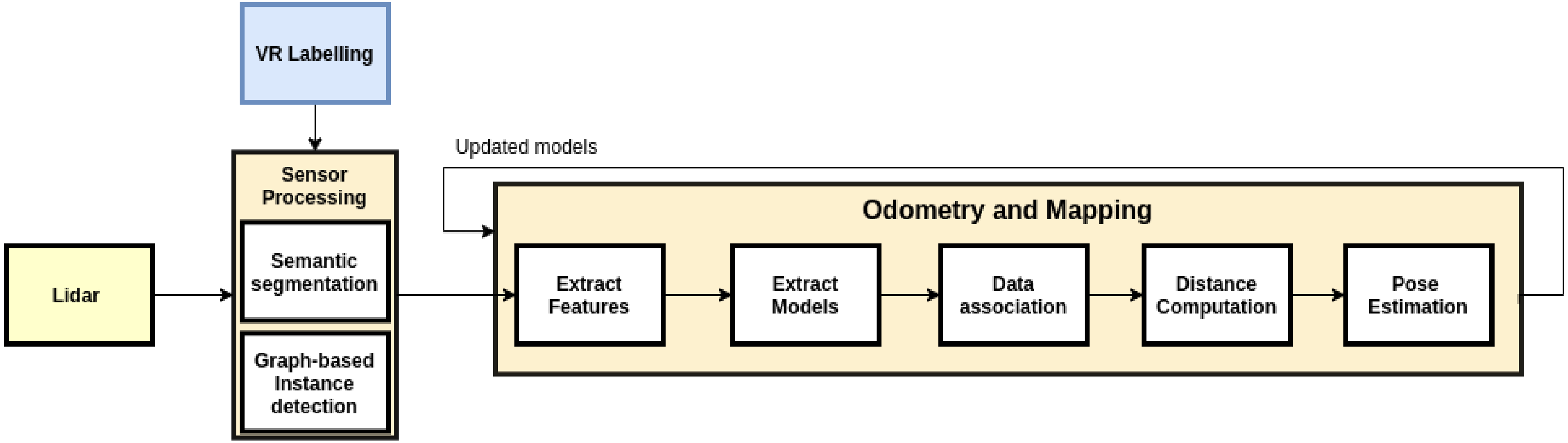
Xu Liu, Steven W. Chen, Shreyas Aditya, Nivedha Sivakumar, Sandeep Dcunha, Chao Qu, Camillo J. Taylor, Jnaneshwar Das, and Vijay Kumar

Penn Engineering | GRASP Laboratory
General Robotics, Automation, Sensing & Perception Lab

USDA NIFA grant 2015-67021-23857
under the National Robotics Initiative

Liu, X., Chen, S. W., Aditya, S., ... & Kumar, V. (2018, October). Robust fruit counting: Combining deep learning, tracking, and structure from motion. In 2018 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS) (pp. 1045-1052). IEEE.

Semantic Lidar Odometry and Mapping



S. W. Chen, G. V. Nardari, E. S. Lee, C. Qu, X. Liu, R. F. Romero and V. Kumar, "SLOAM: Semantic Lidar Odometry and Mapping for Forest Inventory," in *IEEE Robotics and Automation Letters*, vol. 5, no. 2, pp. 612-619, April 2020

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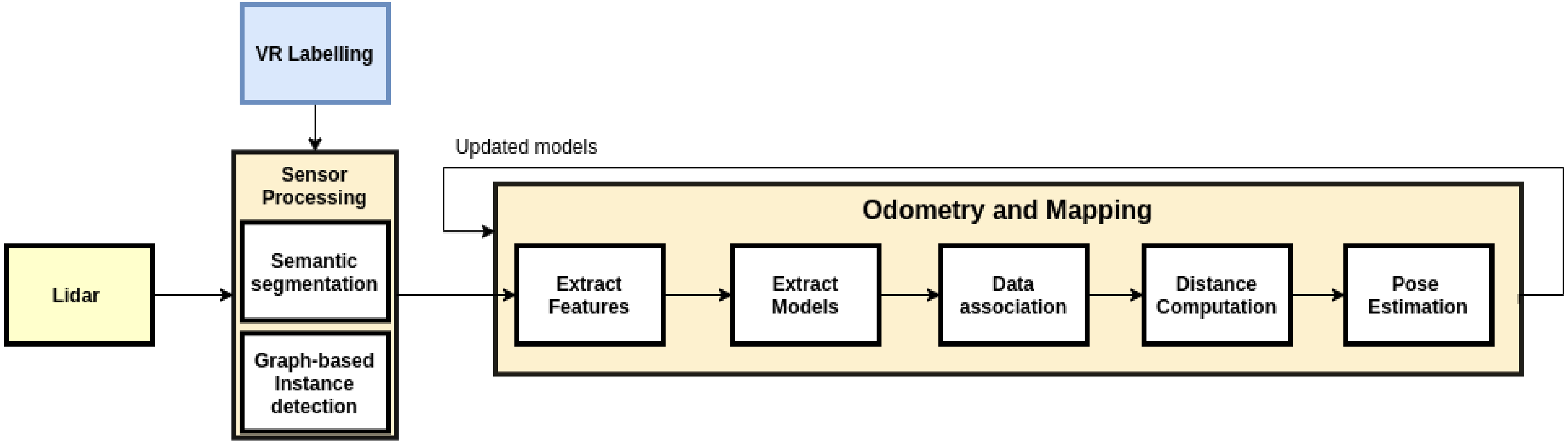

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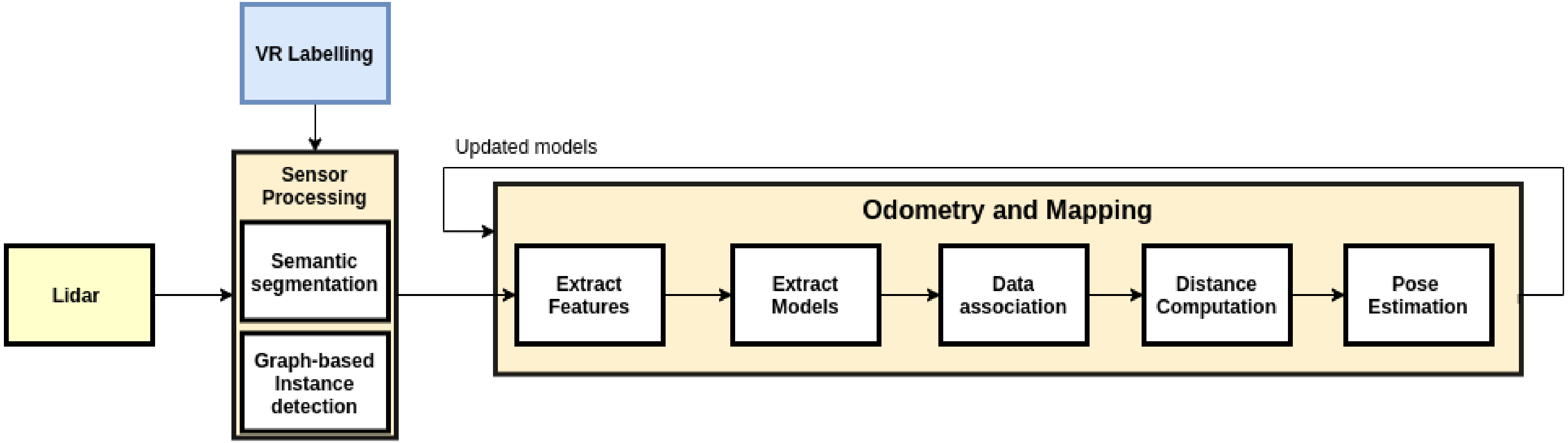

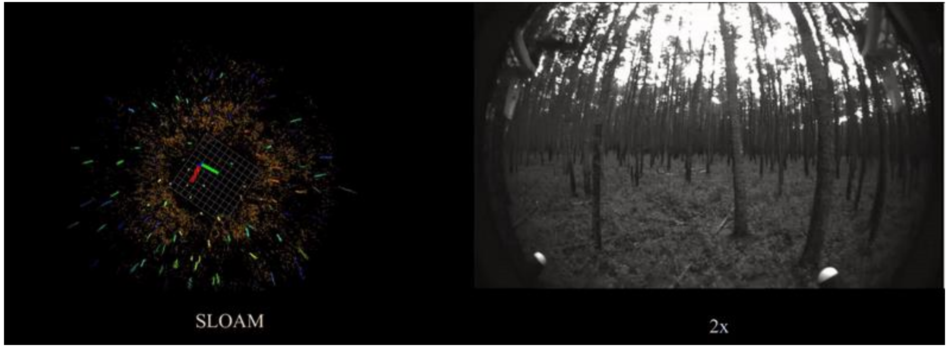

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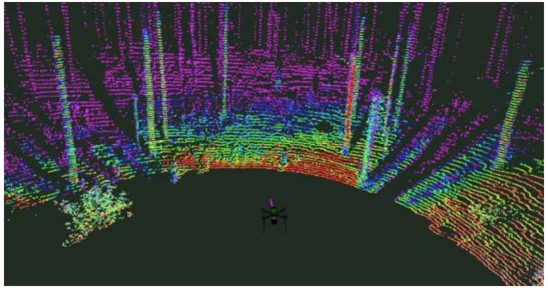
Real-world Experiments

Pictures of the forest
(where our experiments are conducted)

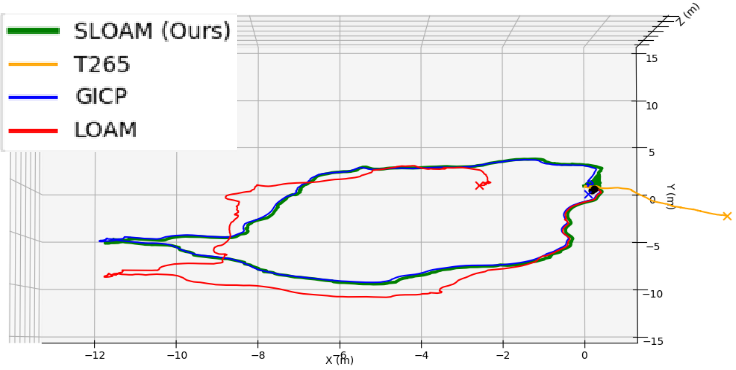
Autonomous under-canopy flight

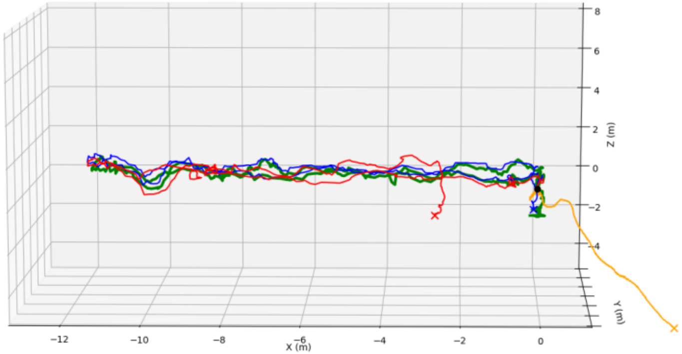


UAV and forest map visualization

Semantic Lidar Odometry and Mapping

Odometry Comparison





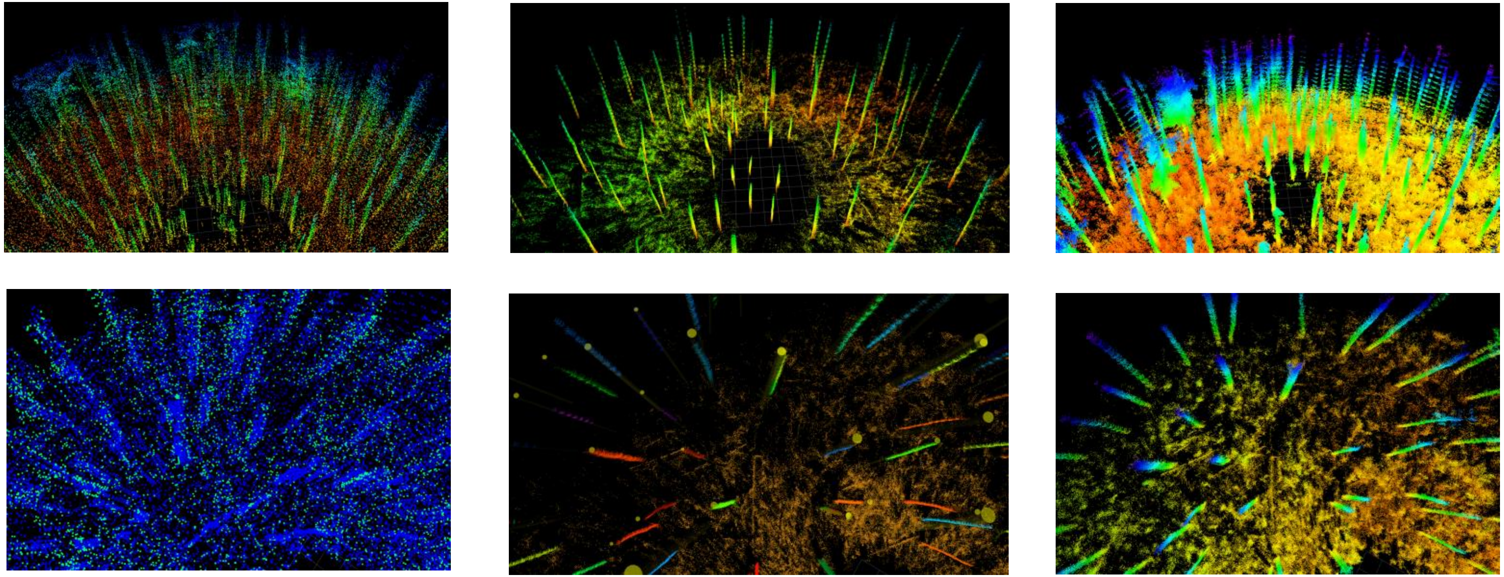
Method	Distance from the goal (m)	Error
Ours	0.37	0.58%
GICP	0.41	0.63%
A-LOAM	2.75	4.24%
T265 (VIO)	> 100	> 100%

Semantic Lidar Odometry and Mapping

Map Comparison

UAV dataset:

Handheld dataset:



A-LOAM | Ours | G-ICP

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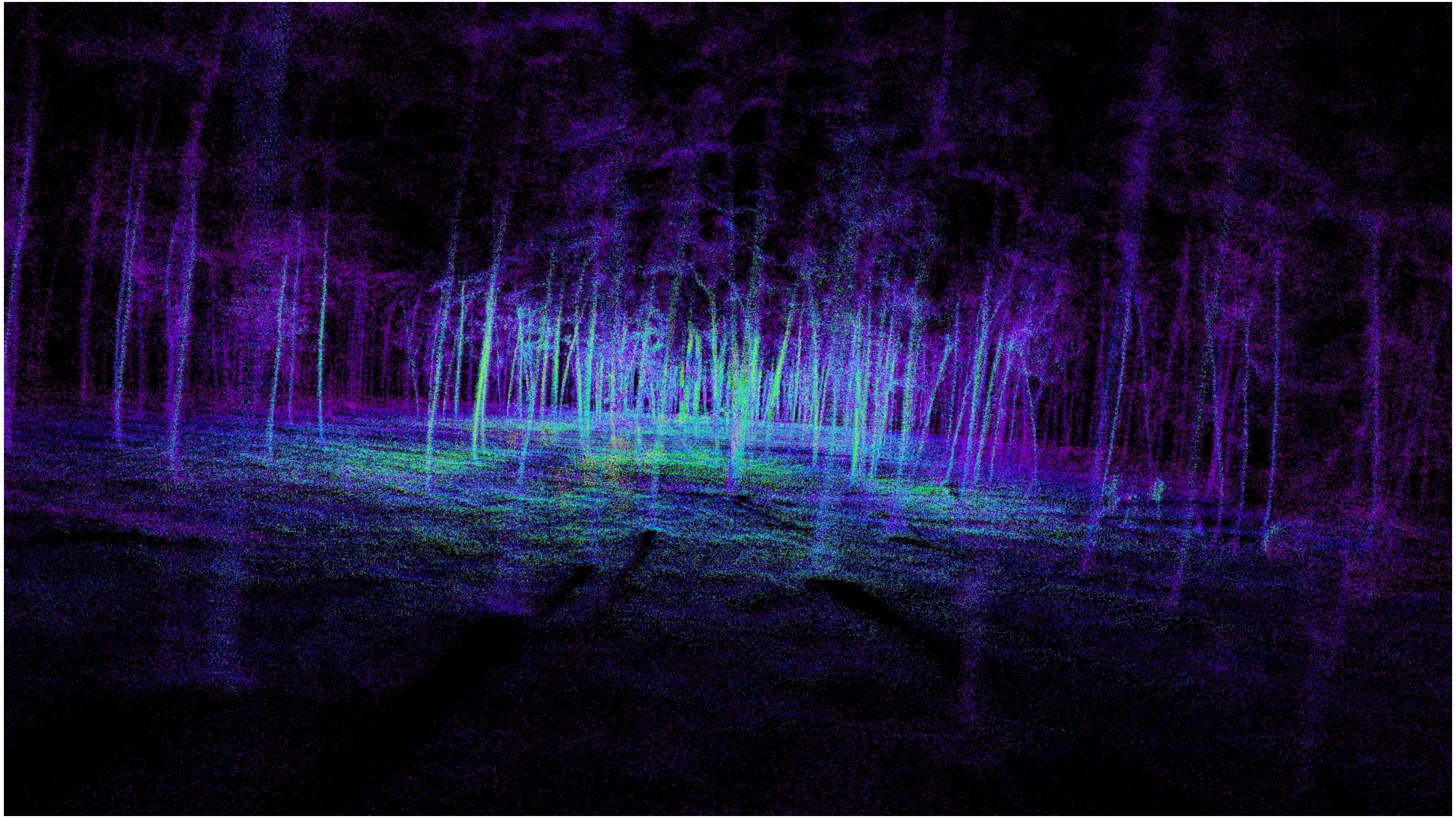
High-fidelity 3D reconstruction



High-fidelity Simulated Environments

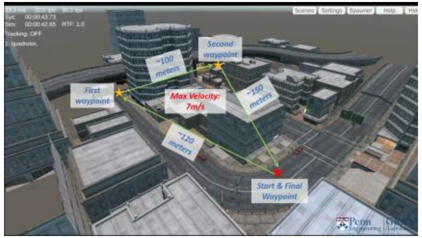
DCIST Simulation Testbed(s):

- Unity-based simulation
- Lightweight wrapper to ROS
- Relies on Unity physics (NVIDIA PhysX)
- Sensors:
  - RGB Cameras, Depth Cameras
  - 3D LIDAR, IMU
  - Wheel speed/torque
- Platforms:
  - Generic Quadrotor
  - Clearpath Husky, Warthog
- Simulated wireless communication
- Multiple environments available

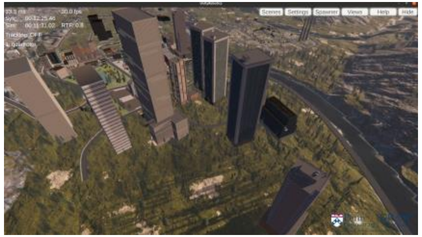
https://www.dcist.org/

Autonomous flights

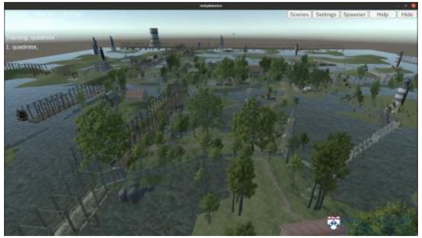
Urban small



Urban large
(> 4 km^2)



Rural



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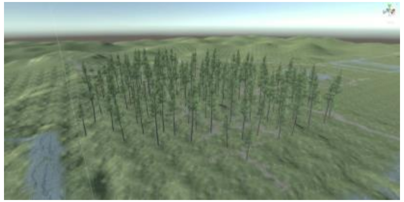
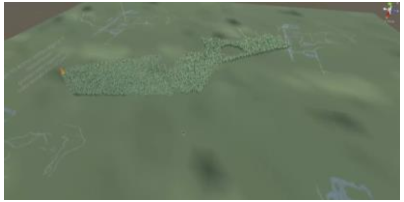
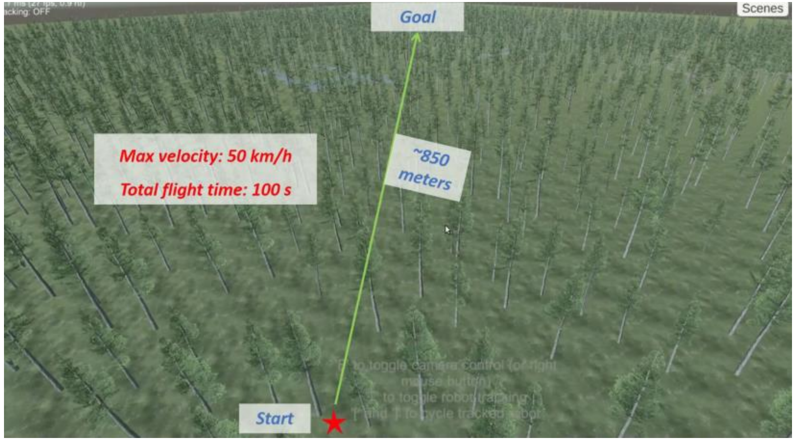


Small forest (~100 trees)



Large forest (~12k trees)



Autonomous flight in simulated forests

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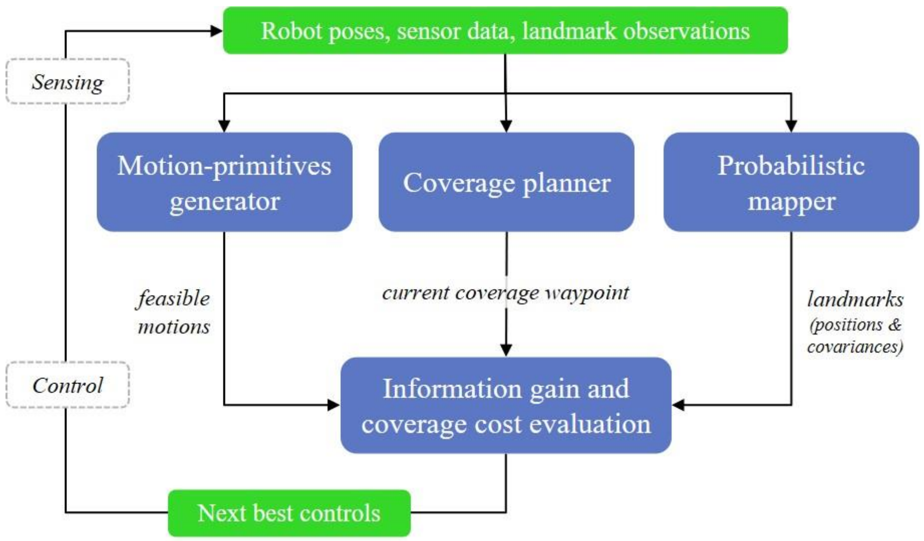
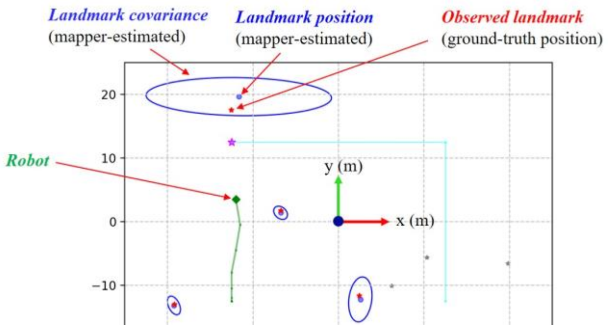
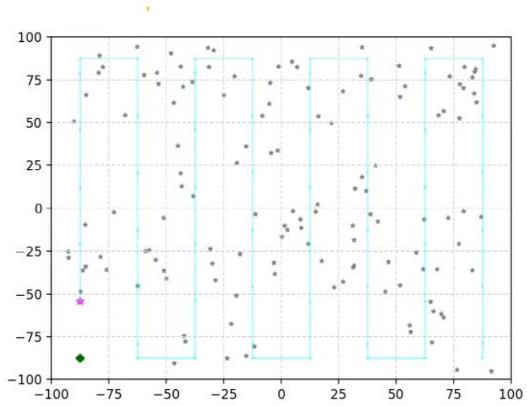
Active Mapping





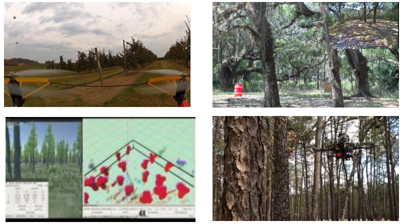
Environment representation



Qualitative results

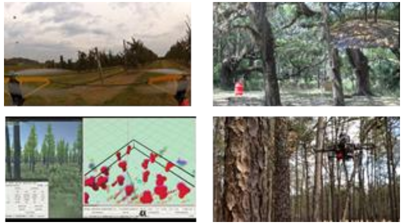
Conclusion and Future Work

Conclusion

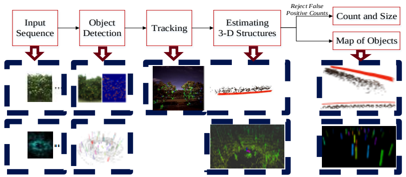


Large-scale autonomy

Conclusion



Large-scale autonomy



Semantic mapping

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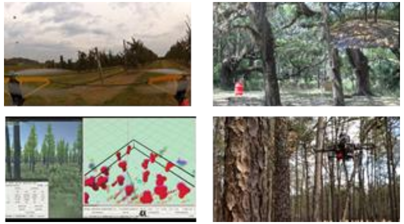
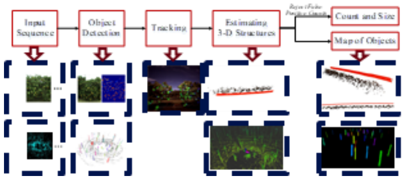
Conclusion



Large-scale autonomy



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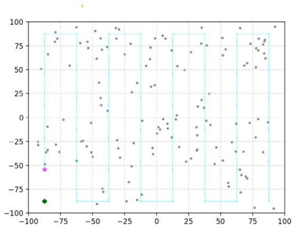
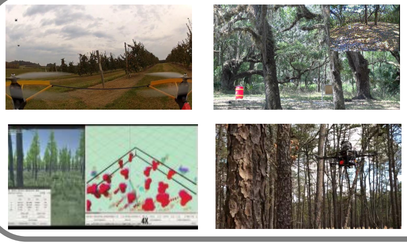
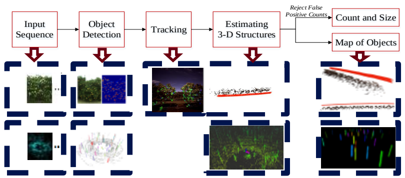


Active mapping

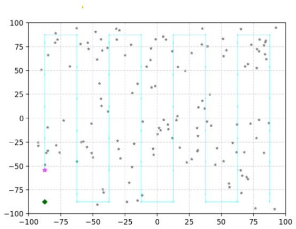
Future Work: Large-scale active semantic mapping



Large-scale autonomy



Semantic mapping



Active mapping

Close the perception-action loop

Large-scale active semantic mapping

Future Work: Cross-view collaborative mapping

Overcanopy Images

3D Reconstruction

Potential solution for localization

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Guilherme V. Nardari, Avraham Cohen, Steven W. Chen, Xu Liu, Vaibhav Arcot, Roseli A. F. Romero, Vijay Kumar, "Place Recognition in Forests With Urquhart Tessellations," in *IEEE Robotics and Automation Letters*, Volume: 6, Issue: 2, April 2021

Thank you!