Towards Safe and Efficient Through-the-Canopy Autonomous Fruit Counting with UAVs

Berkeley UNIVERSITY OF CALIFORNIA

Teaya Yang, Roman Ibrahimov, and Mark W. Mueller

Department of Mechanical Engineering, UC Berkeley

Goal: Develop an autonomous system for fruit counting through RGB images with a focus on through-the-canopy data collection.

Significance: Enables efficient yield estimation for large-scale orchards.

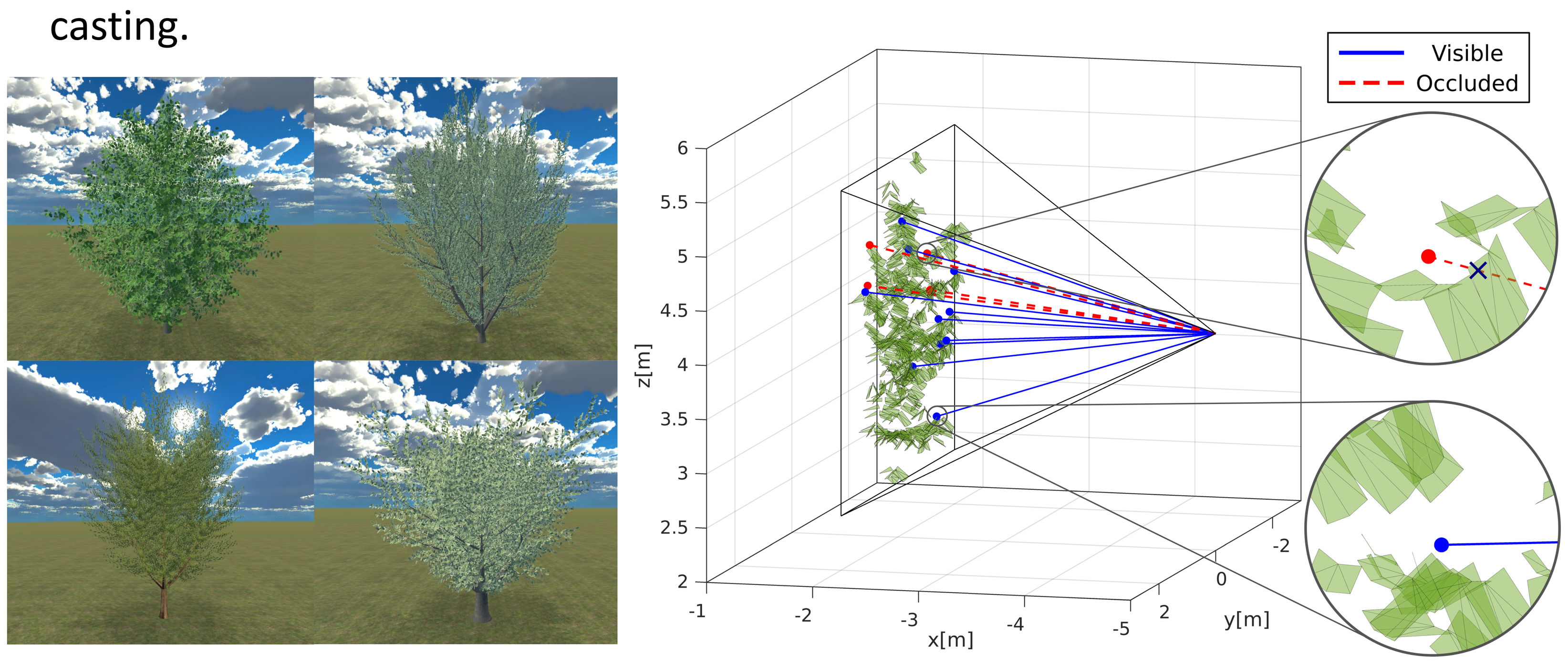
Approach: (a) High-fidelity simulation for informed path planning (b) Autonomous canopy-level navigation for data collection (c) Robust fruit counting using state-of-the-art computer vision tools

Motivation

- **Yield estimation** is important for making management decisions such as harvest scheduling, labor allocation, and storage strategies.
- UAV flight at canopy height **minimizes visual obstructions** compared to ground vehicles or over-the-canopy aerial imagery, offering additional viewpoints for data collection.
- Effective **obstacle avoidance** and accurate **state estimation using onboard sensor** data are essential for navigating dense canopies and tight tree spacing in industrial-scale orchards.

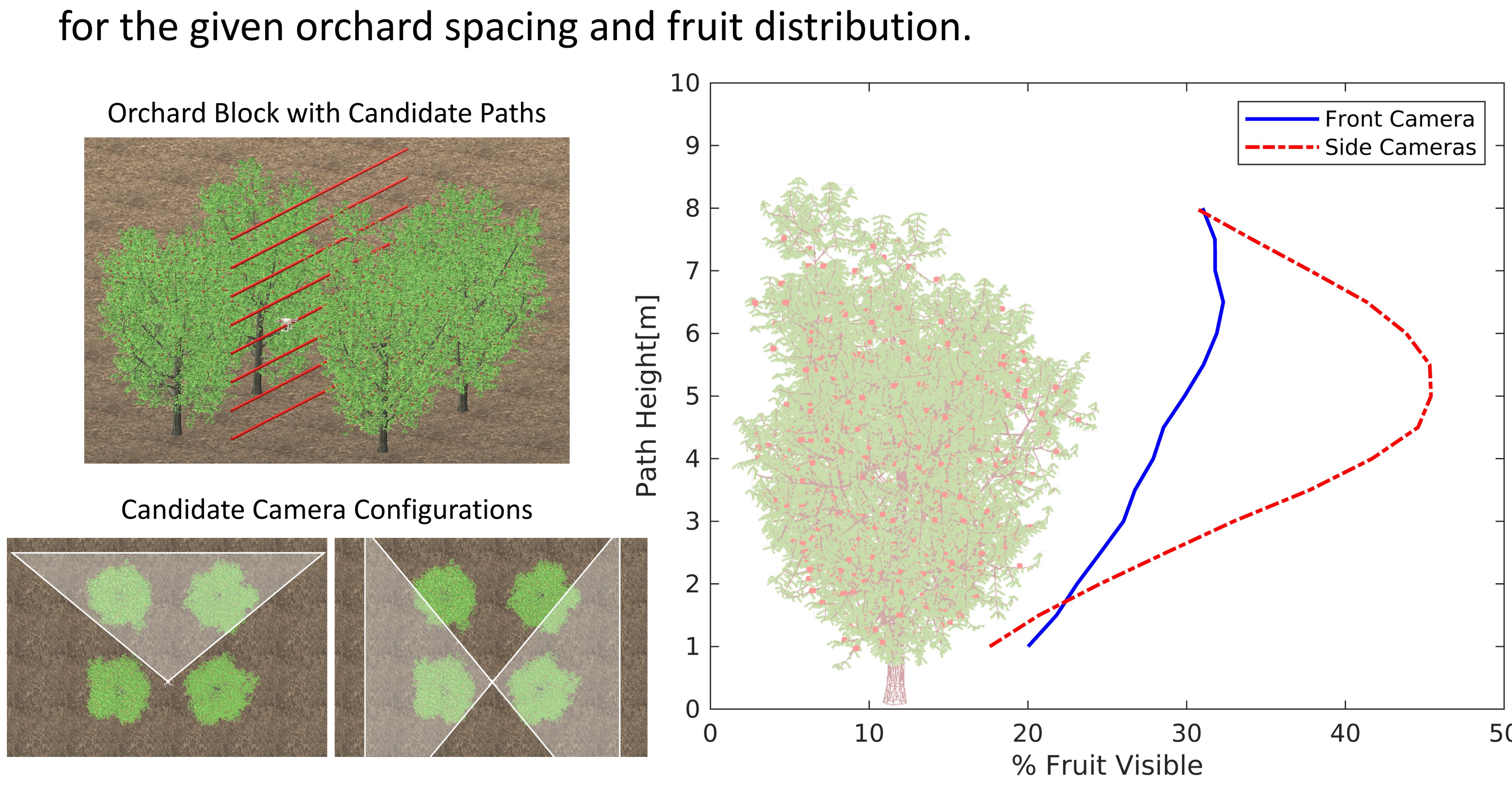
Simulation with Occlusion Model

- Fruit tree mesh models are generated using HELIOS [1], with sampled tree architectures and known geometries.
- **Ground truth positions of visible fruits** at a given viewpoint are computed via ray casting.



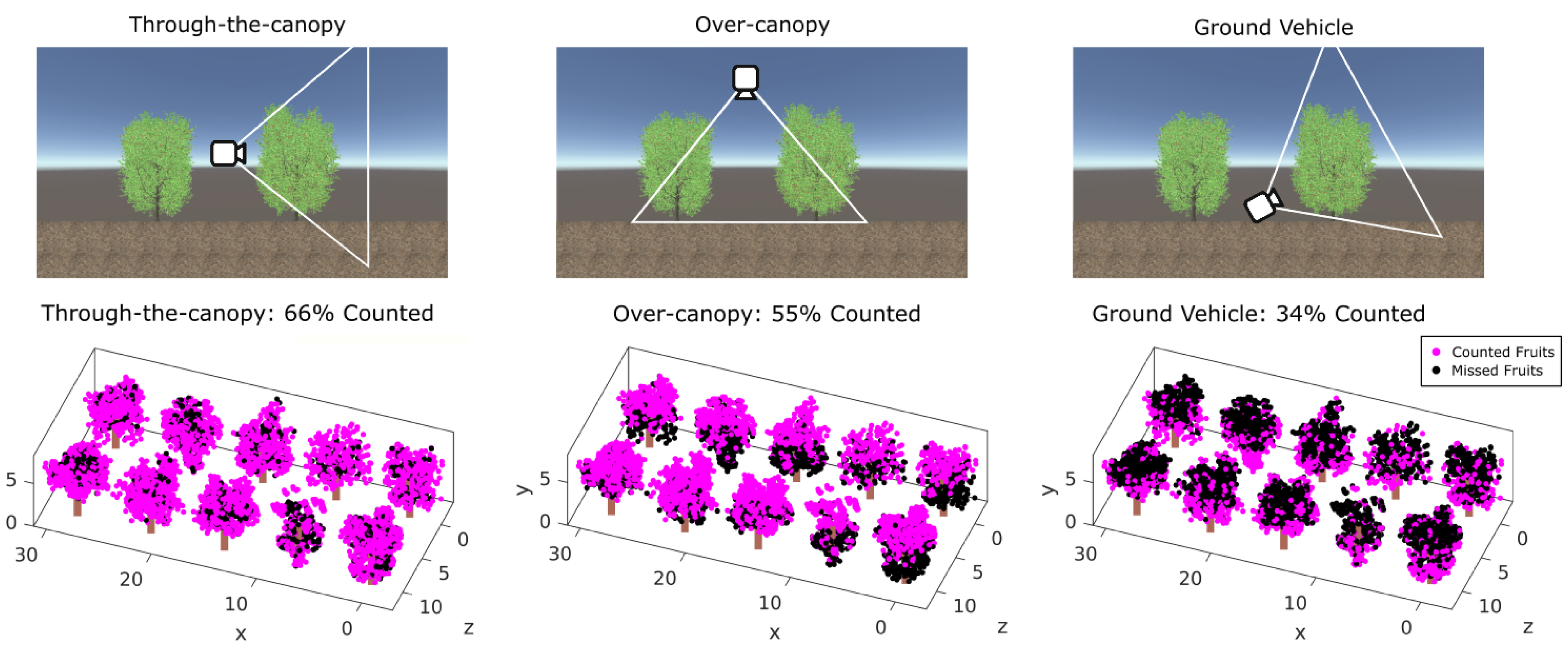
Global Path Planning

- Optimal flight height and camera orientations are tested using randomly generated orchard blocks with 7.6m × 7.3m spacing.
- The mean visible fruit percentage across 10 generated orchard blocks suggests that mounting RGB cameras on the sides of the vehicle provides an advantage for fruit counting compared to using a single front-facing camera.
- The results further show that, for each configuration, an **optimal height** exists for the given orchard spacing and fruit distribution.



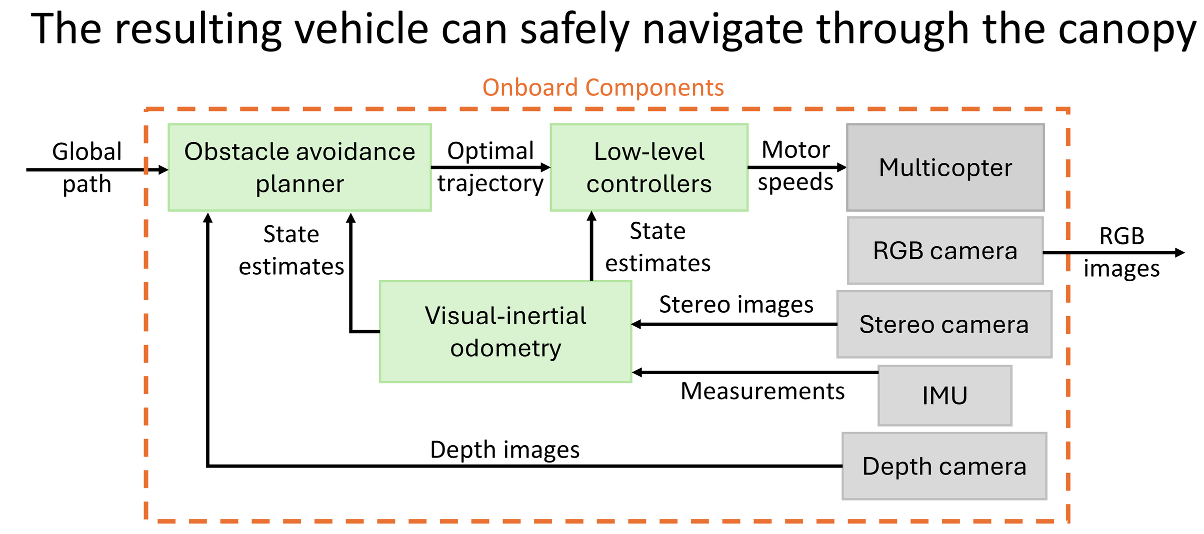
Advantage of Canopy-Height Flight

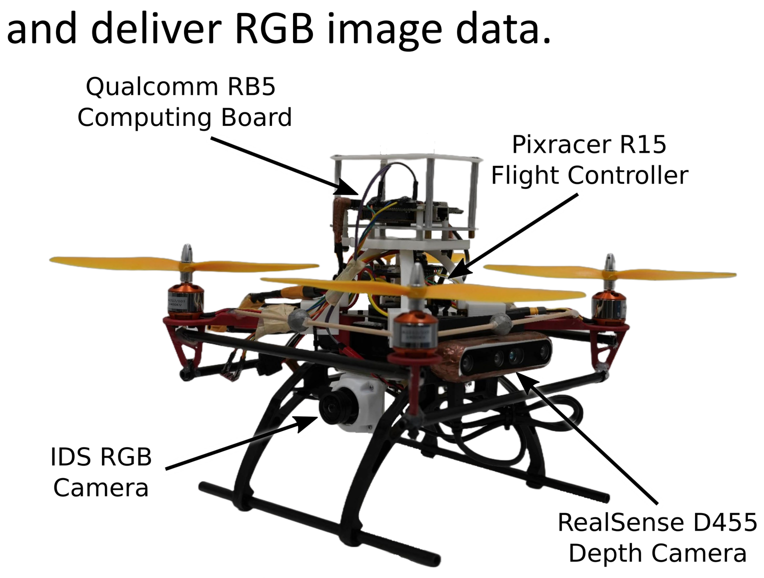
- Fruit counting results for a sample orchard for three trajectories are compared. Vehicle height and camera orientation are chosen to represent viewpoints provided by an UAV flying at canopy height, an UAV flying over the tree canopy, and a ground vehicle.
- The canopy-height trajectory was able to count 66% of the total number of fruit in the simulated orchard, compared to 55% and 34% from the over-the-canopy view and ground vehicle view, respectively.

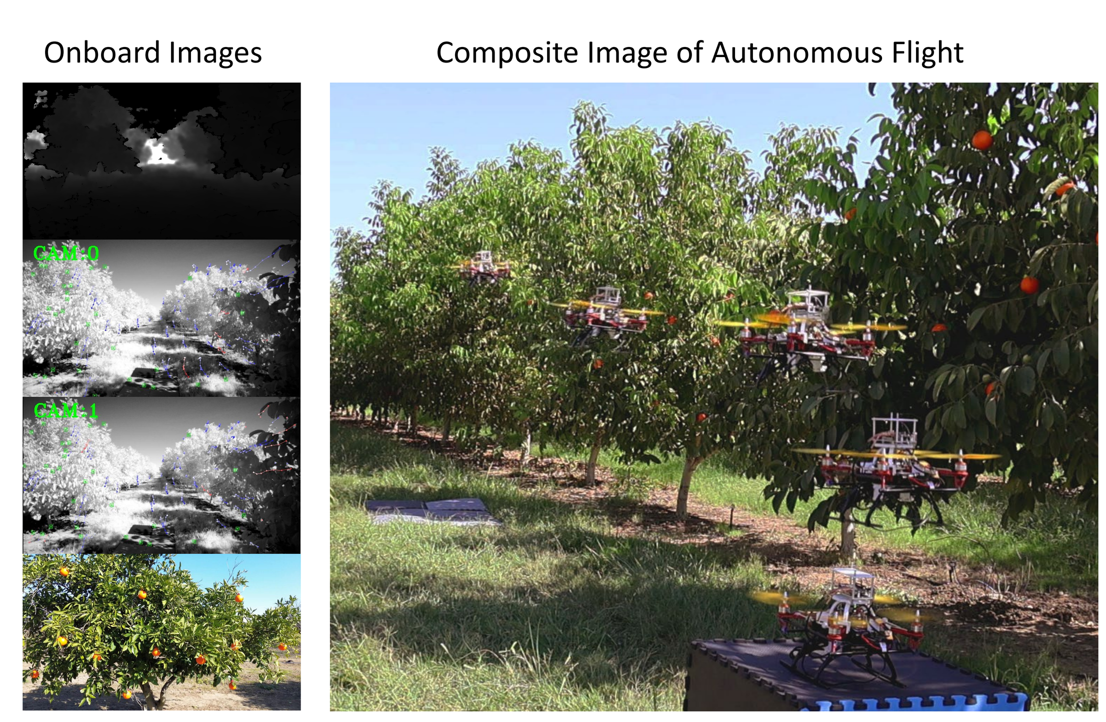


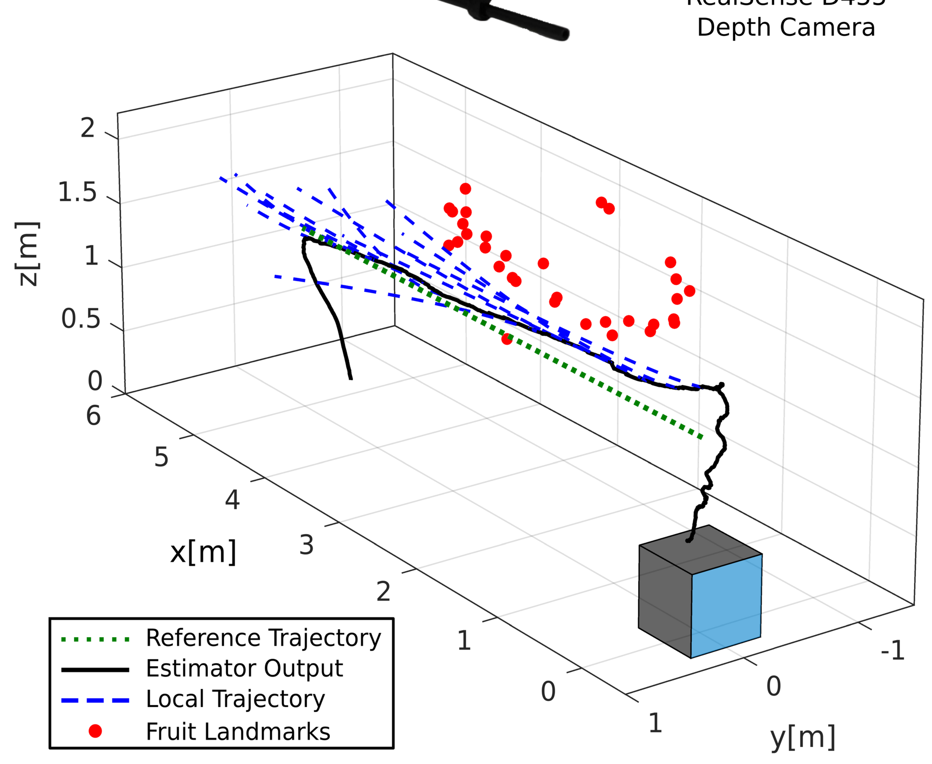
Autonomy Design for Data Collection

- The **obstacle avoidance planner** in [2], which uses depth image input, enables our UAV to fly at canopy height between tree rows.
- We use **visual-inertial odometry (VIO)** [3] for state estimation in outdoor environments.
- The resulting vehicle can safely navigate through the canopy and deliver RGB image data.



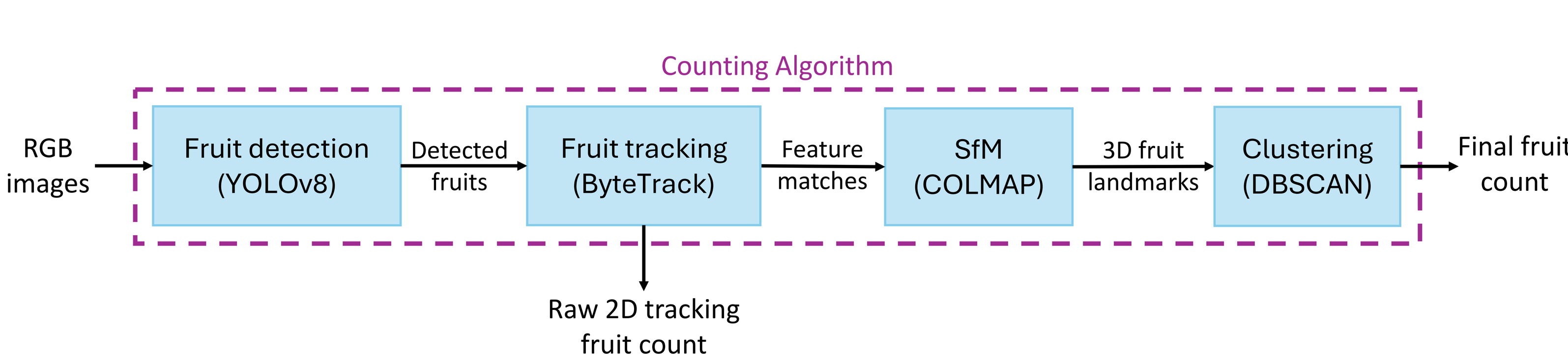


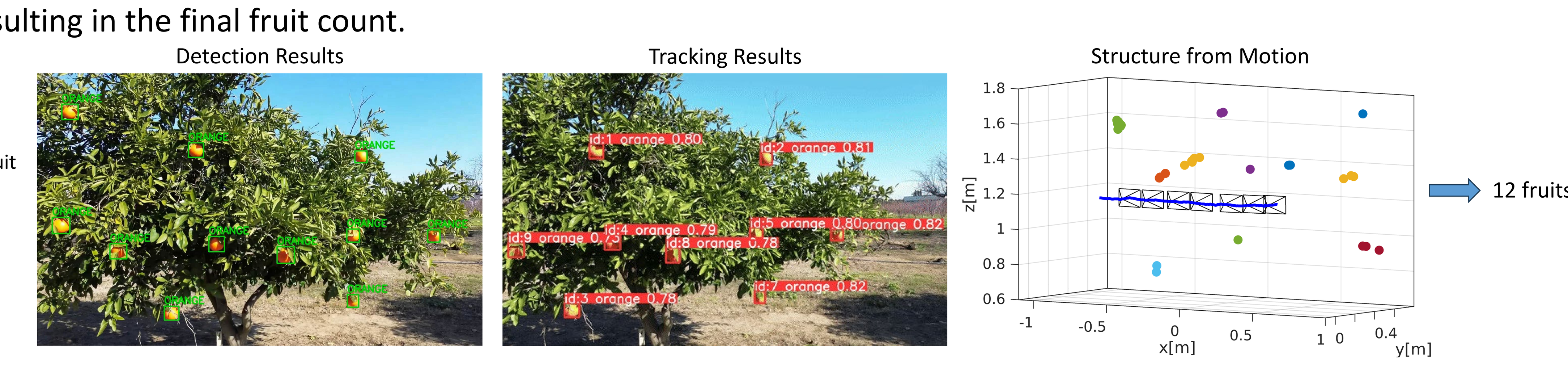




Robust Fruit Counting

- We adopt the fruit counting workflow outlined in [4] to ensure accurate counting from the collected data and to minimize double counting.
- State-of-the-art computer vision toolboxes are employed, including a fine-tuned YOLOv8 [5] for fruit detection and ByteTrack [6] for tracking across consecutive frames.
- The outputs of the tracking algorithm serve as input correspondences for the structure-from-motion process, in which COLMAP [7] estimates the camera extrinsics and reconstructs the 3D locations of fruit landmarks.
- The 3D fruit locations are subsequently used to **eliminate double counting**, resulting in the final fruit count.





References

1. Brian N Bailey. “Helios: A scalable 3D plant and environmental biophysical modeling framework”. In: Frontiers in Plant Science 10 (2019), p. 1185.
2. N. Bucki, J. Lee, and M. W. Mueller, “Rectangular pyramid partitioning using integrated depth sensors (RAPPIDS): A fast planner for multicopter navigation,” IEEE Robotics and Automation Letters, vol. 5, no. 3, pp. 4626–4633, 2020.
3. P. Geneva, K. Eckenhoff, W. Lee, Y. Yang, and G. Huang, “OpenVINS: A research platform for visual-inertial estimation,” in 2020 IEEE International Conference on Robotics and Automation (ICRA), pp. 4666–4672, 2020.
4. X. Liu, S. W. Chen, C. Liu, S. S. Shivakumar, J. Das, C. J. Taylor, J. Underwood, and V. Kumar, “Monocular camera based fruit counting and mapping with semantic data association,” IEEE Robotics and Automation Letters, vol. 4, no. 3, pp. 2296–2303, 2019.
5. J. Redmon, “You only look once: Unified, real-time object detection,” in Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, 2016.
6. Y. Zhang, P. Sun, Y. Jiang, D. Yu, F. Weng, Z. Yuan, P. Luo, W. Liu, and X. Wang, “ByteTrack: Multi-object tracking by associating every detection box,” in European Conference on Computer Vision, pp. 1–21, 2022.
7. J. L. Schönberger and J.-M. Frahm, “Structure-from-motion revisited,” in Conference on Computer Vision and Pattern Recognition (CVPR), 2016.

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