CropFollow++: Robust Under-Canopy Navigation with Keypoints

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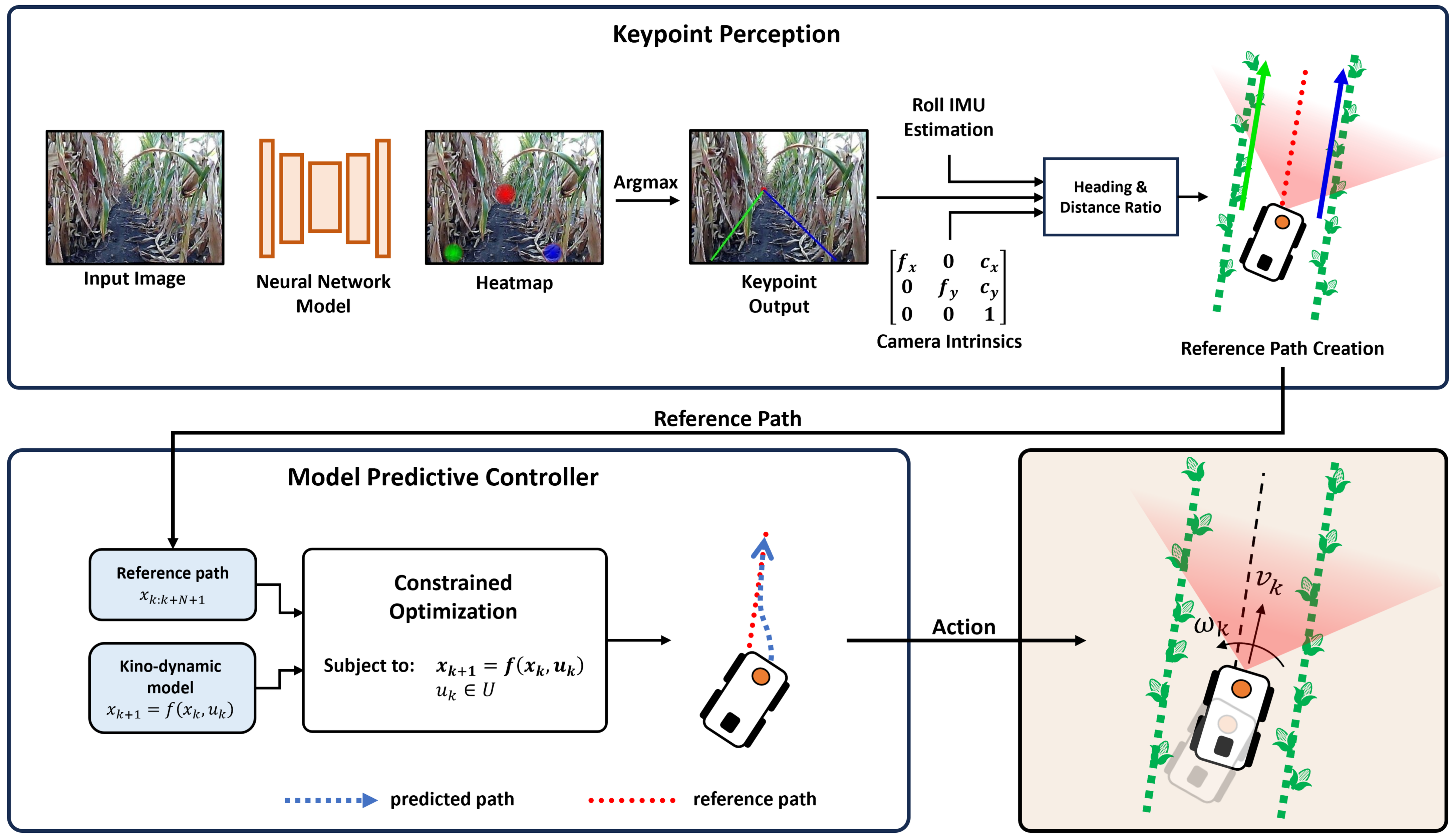
Motivation

- Autonomous under-canopy robots can enable various applications such as high throughput phenotyping, cover crop planting.
- Under-canopy navigation is challenging because of the noise in RTK-GPS and large clutter in the visual scene.
- Prior state-of-the-art learning based visual navigation system called CropFollow proposed an end-to-end perception approach.
- CropFollow is sensitive to variations in intrinsics across cameras, does not provide a measure of uncertainty to detect out-of-distribution scenarios like occlusion, and is less interpretable.
- We propose a more robust visual navigation system *CropFollow++* to address the above limitations.

CropFollow++ overview



- CropFollow++ uses a modular perception approach with a Convolutional Neural Network (CNN) to predict three semantic keypoints; these keypoints along with the roll angle estimate from IMU and known camera intrinsics are used to create the reference path (middle of lane) for the robot.
- Model Predictive Controller (MPC) steers the robot towards the reference path by controlling the linear and angular velocity of the robot.

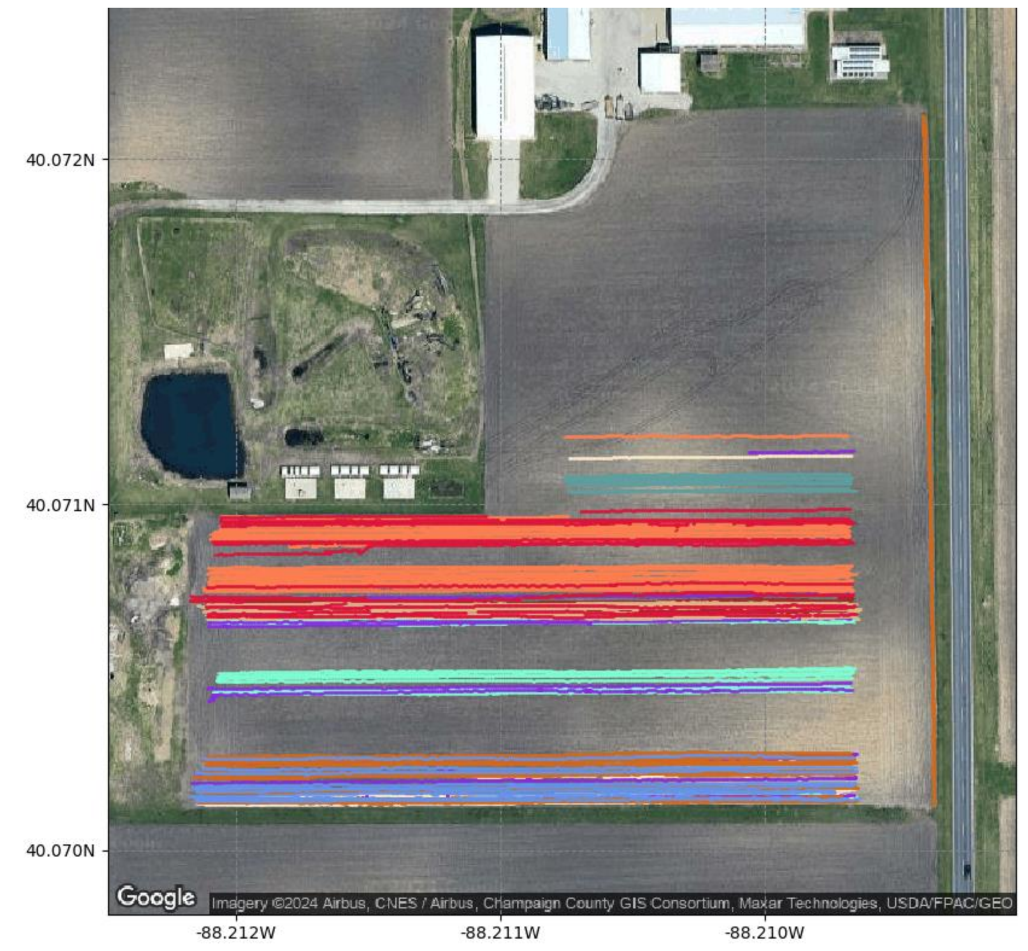
Out-of-distribution (OOD) detection


Camera occlusion


Robot outside crop rows

Keypoint representation enables detection of OOD scenarios using the variance of keypoint heatmaps.

Large-scale tests on Cover Crop Robots



- We tested CropFollow++ on three cover crop robots for more than 25km with autonomous crash detection and recovery using back camera.
- 33 human interventions were needed in total.
- The longest autonomous run without intervention was 3.57km.

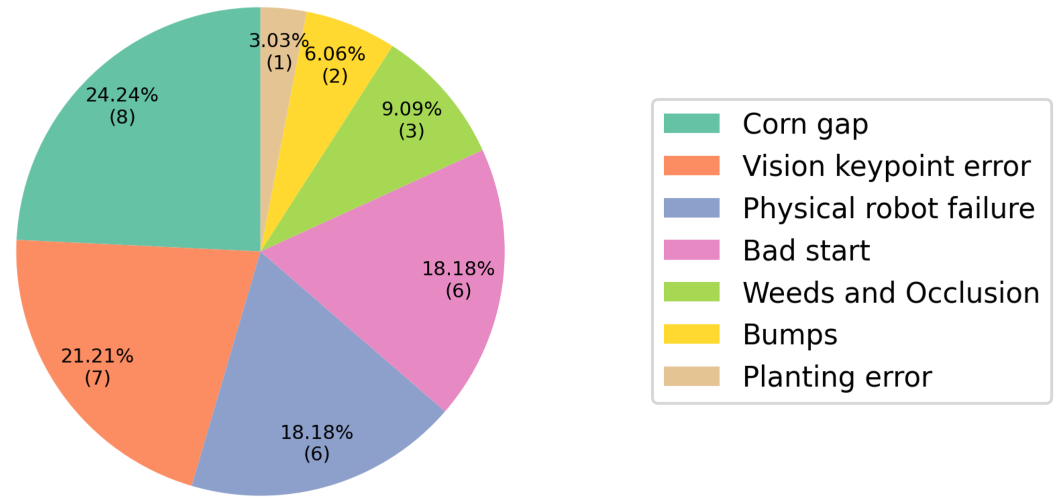


Figure shows distribution of various causes of failures that needed human intervention.

Field validation tests

Figure shows visualization of predicted keypoints during field tests. Middle column represents the model predictions.

	Length of experiment [m]	Number of interventions		Max distance without interventions [m]	
		CropFollow++	CropFollow	**CropFollow++**	CropFollow
Run 1	420	2	2	412	310
Run 2	420	5	8	262	115
Run 3	420	2	10	366	165
Run 4	180	1	7	170	74
Run 5	420	3	6	390	260

<u>CropFollow++ 143 meters/ intervention</u> vs CropFollow 56 meters/ intervention

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