Learned Visual Navigation for Under-Canopy Agricultural Robots I ILLINOIS

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MOTIVATION

- Autonomous under-canopy robots can enable several applications in commodity row-crops (corn, soybean etc.):
 - High-throughput plant phenotyping
 - Ultra-precise pesticide treatments
 - Mechanical weeding
 - Plant manipulation
 - Cover crop planting



Phenotyping robot



Cover crop planting robot

UNDER-CANOPY NAVIGATION CHALLENGES

- GPS navigation is not reliable.
- LiDAR is costly, captures only geometric and not semantic information.
- Large variability and clutter limits the use of classical computer vision





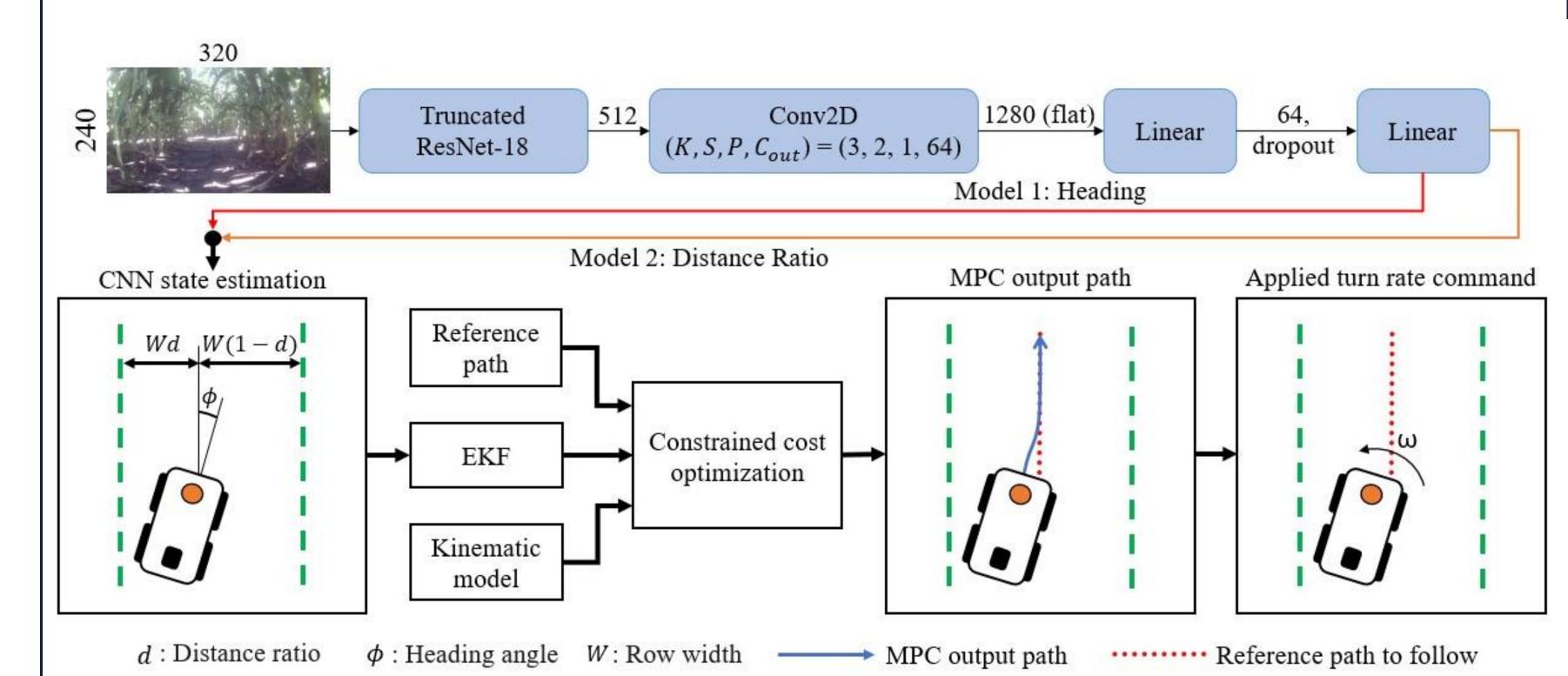




View from on-board camera of the robot

OUR APPROACH:

Vision and learning based navigation system - CropFollow



- 2 convolutional networks output robot heading, φ and distance ratio, $d = d_I/(d_L + d_R)$
- Sensor fusion with IMU using extended Kalman filter
- Optimal control using model predictive controller
- PID for low level control

d_{l} $\phi \uparrow_{d_{R}}$

GROUND TRUTH FROM VANISHING LINES

- Labeled 25296 images of corn and 10685 images of soybean with vanishing lines
- Used projective geometry on the annotated vanishing lines to extract heading and distance ratio labels



Early season annotation



Late season annotation

Project website with data and videos: https://ansivakumar.github.io/learned-visual-navigation/

RESULTS

FIELD VALIDATION

CropFollow vs LiDAR (in number of human interventions needed)

Growth Stage	Length (m)	LiDAR w/ IMU	LiDAR w/o IMU	CropFollow w/ IMU	CropFollow w/o IMU
Early	1120	-	-	3	4
Late	3726	13	72	7	8

CropFollow w/IMU – <u>485 meters/intervention</u> LiDAR w/ IMU – 286 meters/intervention

TEST IN DIVERSE ENVIRONMENTS

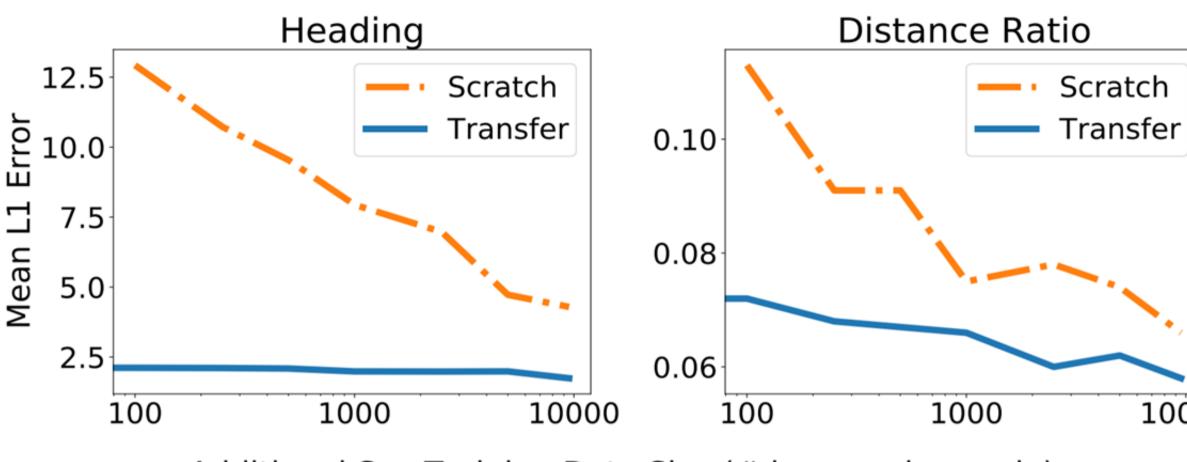


View from on-board camera used for navigation

GENERALIZATION TO SOYBEAN

 We note strong transfer of the model trained on Corn to Soybean even without retraining





Additional Soy Training Data Size (# images, log scale)