Autonomous Mobile Robot for In-field Phenotyping: System Design, Visual Navigation, and Field Mapping

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Background and Objectives

Automatic phenotyping technologies have been shown to accelerate crop breeding by replacing time-consuming manual measurements with a uniform standard. However, the current systems are heavy and expensive, which limits their commercialization potential. To address this issue, we aim to develop an affordable, lightweight robot for automatic phenotyping, focusing on two key aspects: visual navigation and field phenotyping.

1) Develop a light-weight and flexible phenotyping robot to perform field phenotyping tasks;
2) Design a vision-based navigation algorithm and evaluate its efficacy;
3) Develop a phenotyping pipeline to realize 3D field mapping and seedling phenotyping traits extraction

System Design

- Modular agricultural robotic system with ROS-based control architecture
- Low-cost, lightweight, solar-powered field phenotyping robot
- Flexible motion with 4-steering-4-driving configuration
- Multi-camera sensing system: two for navigation, one for crop/weed detection and mapping

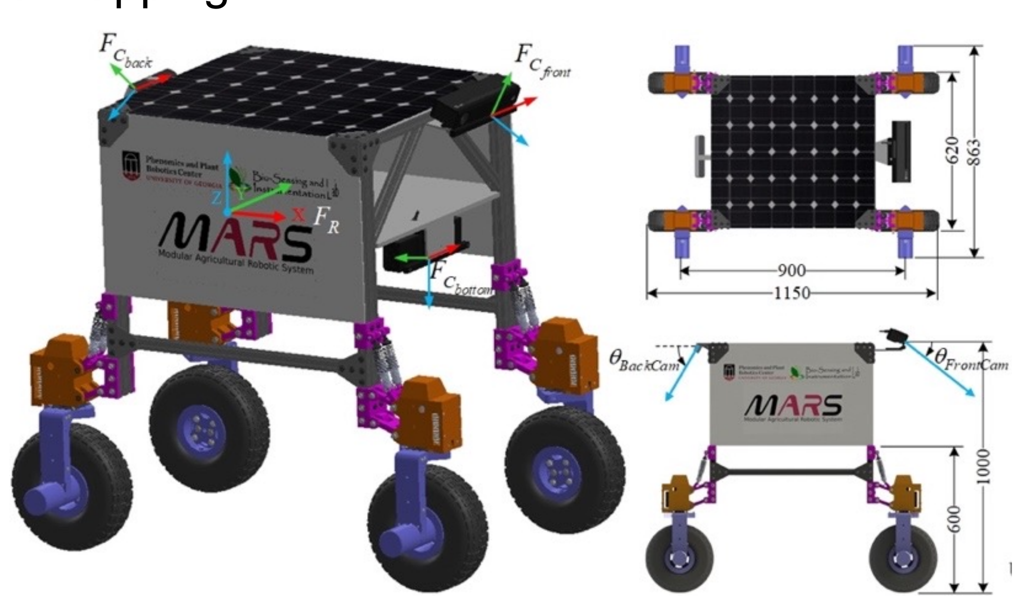

Fig 1. Ground phenotyping robot MARS-PhenoBot

In-field Visual Navigation

The row-planting field can be divided into multiple same subsections, in which robot repeats the same navigation logic. In a subsection, there are three stages:

Stage ①: enters the field and navigates along a row with Front Camera

Stage ②: approaches the end of the row and navigates with Back Camera

Stage ③: transits to the next crop row

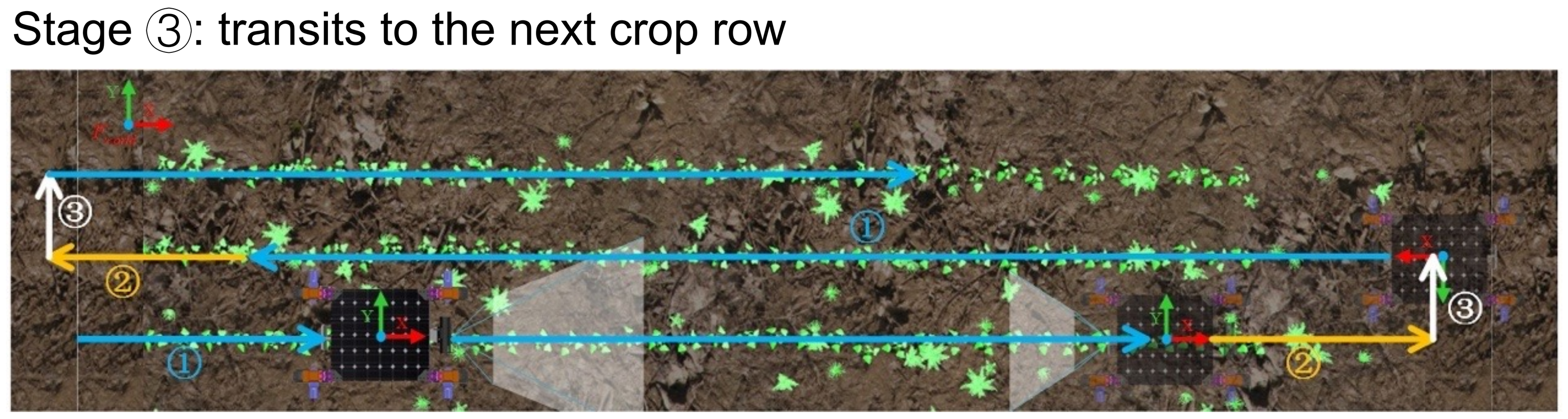

Fig 2. Ground Scheme for navigation in a cotton field

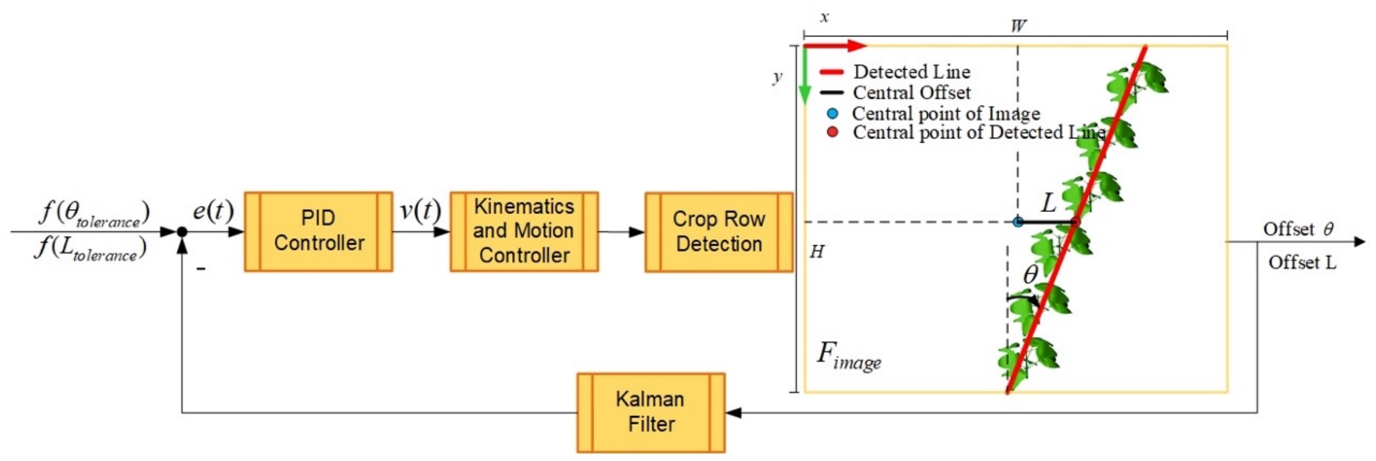

Fig 3. Visual Servo controller for row-following algorithm (Stage ① and ②)

One of the challenges is to recognize the crop row accurately and extracted the offset parameters as the control input of the servo controller. We compared two approaches:

Approach1: Classic image processing approach

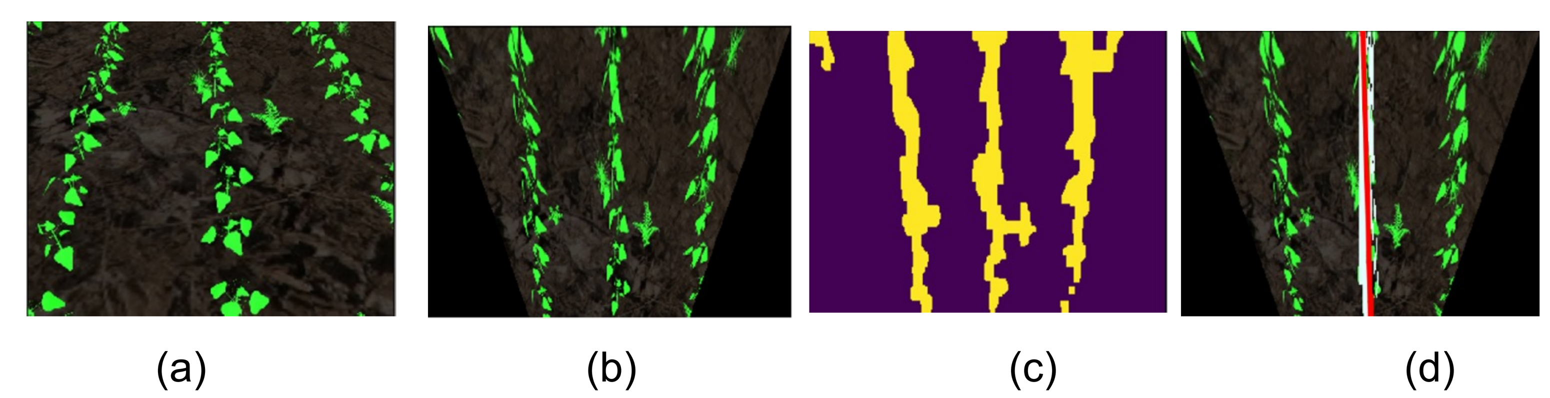

Fig 4. The sequence of crop row detection process. (a) Original Image, (b) Homography Transform, (c) HSV Threshold, (d) Probabilistic Hough Transform

Approach2: Deep learning approach

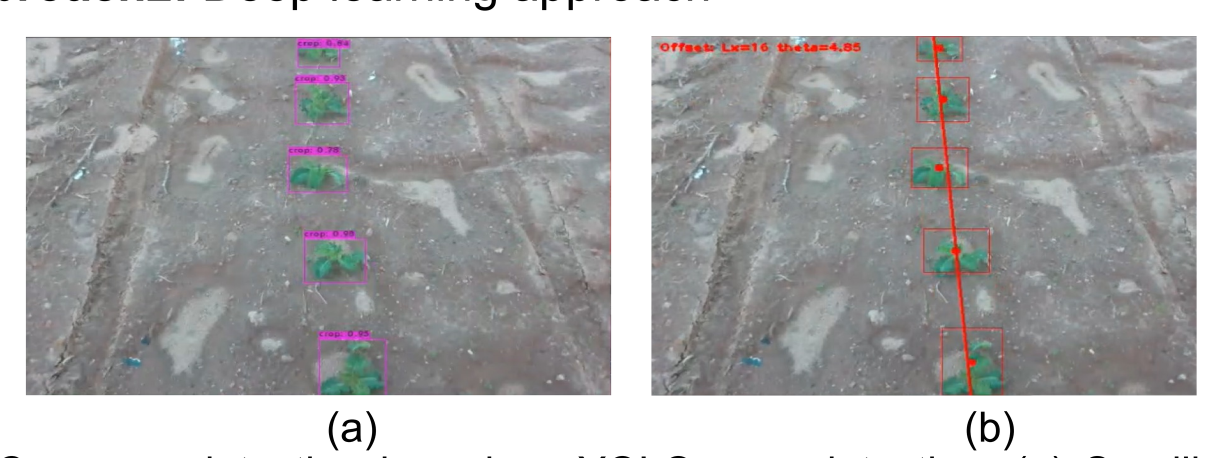

Fig 5. Crop row detection based on YOLO crop detection. (a) Seedling detection based on YOLO (b) Crop row detection with RANSAC algorithm

3D mapping and Phenotyping Analysis

- 3D mapping with RTAB-Map and CloudCompare
- Leaves and trunk Segmentation with PointNet++

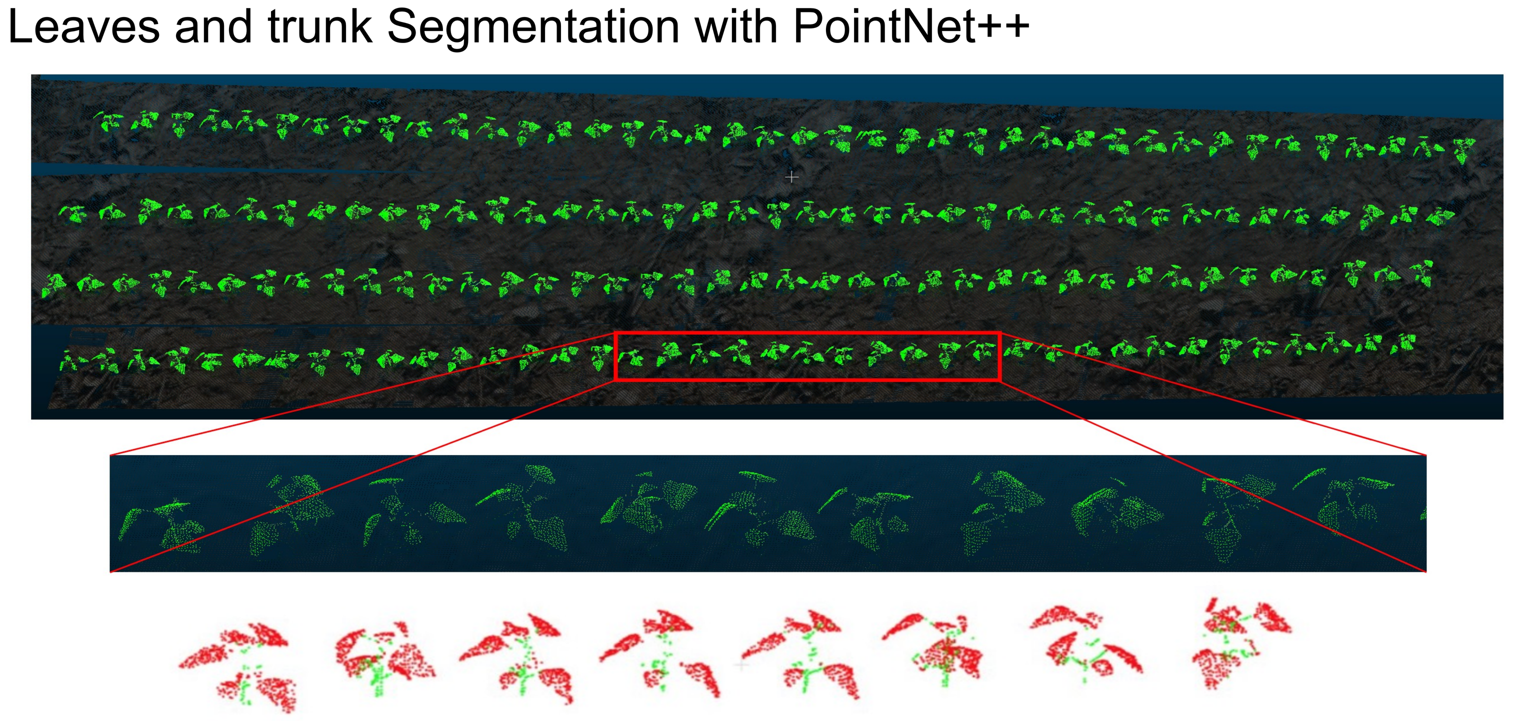

Fig 6. Illustration of the 3D mapping and plant segmentation

Seedling Tracking and Mapping

- YOLO-based detector and DeepSORT-based tracker
- Mapping with 2D-to-3D transform

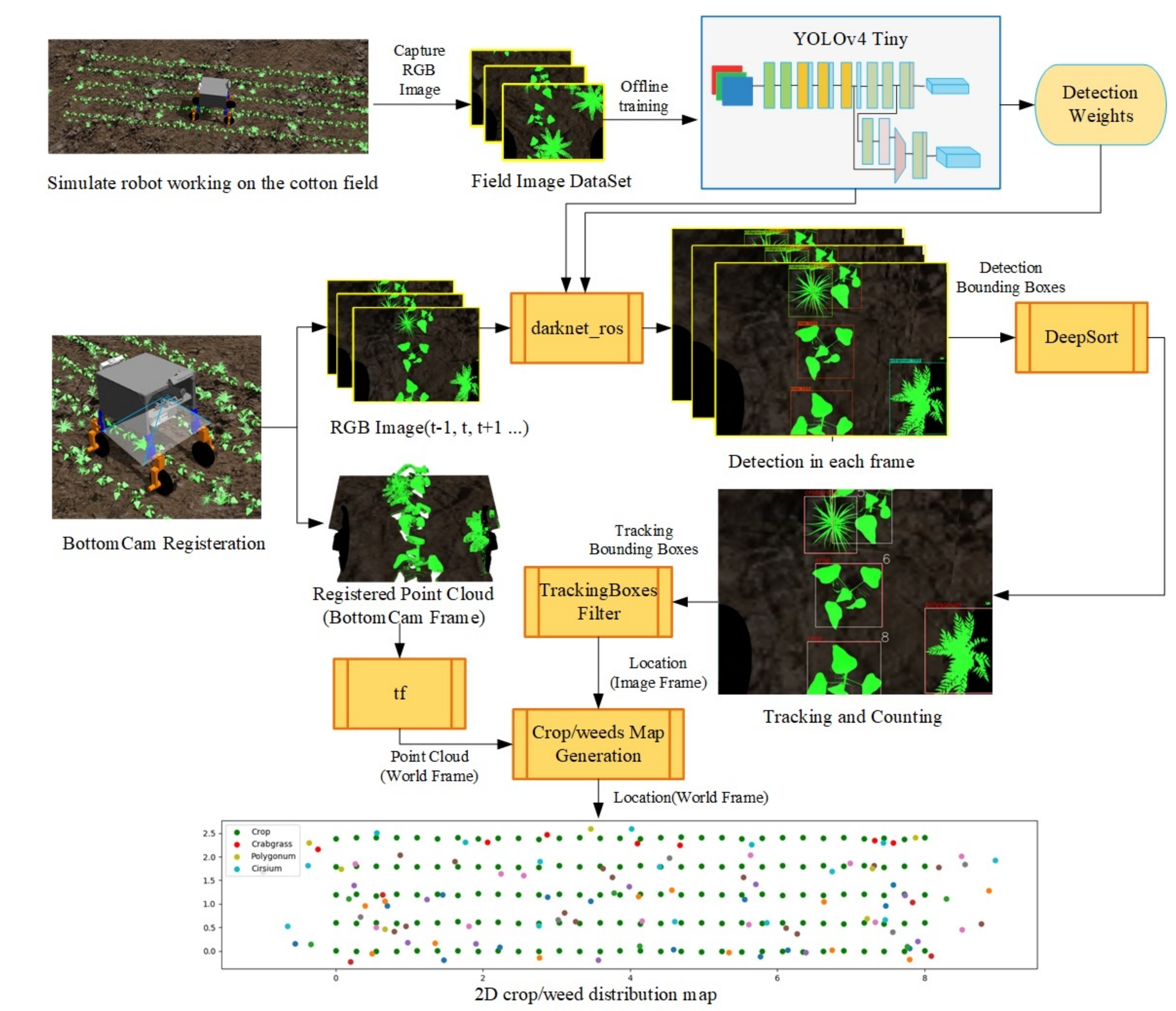

Fig 7. Illustration of the seedling tracking and mapping pipeline

Conclusion & Future Work

MARS-PhenoBot enables to adjust the crop field environment with flexible steering and driving ability. The mechanical system can be further improved for higher system stiffness and stability.

Visual Navigation with front and back camera shows great potential for field navigation without GPS, but recognizing transition locations (end of rows) is difficult. DL-based approach performs better to extract the crop row in weeds environment or varying illumination.

Field Mapping pipeline can achieve real-time online 3D field mapping for large-scale field. With the point cloud segmentation technologies, organ-level phenotyping traits (e.g., leaves, trunk) can be extracted for further breeding analysis.

Acknowledgement

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