Autonomous navigation in cotton fields using deep learning

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Introduction

- **Importance of autonomous navigation in agriculture:**
  - Improves precision agriculture practices (targeted weeding, spraying, harvesting, etc.)
  - Reduce costs and need for human labor.
  - Enhance operation safety and improve productivity
- **Challenges**:
  - Uncertainties of outside environment (weather changes)
  - Inconsistent illumination, shadows
  - Obstacles, occlusion
  - Weeds, crop growth stages, row spacing
- **Possible solutions for autonomous navigation:**
  - GPS navigation – mostly used (Cons: Availability issues due to atmospheric conditions, inability to detect obstacles)
  - Computer vision technologies – e.g., using RGB cameras for color segmentation (Cons: sensitive to weeds, illumination), LIDAR (Cons: expensive)
  - Deep learning – discriminating between rows and paths, e.g., Convolutional neural networks, Semantic segmentation using neural networks
- **Selected solution for this study:**
  - Fully convolutional neural network (FCN) for semantic segmentation model (famously 'U-Net'), was chosen due to its robustness against changes in illumination, weeds presence, shadows, occlusion, and crop growth stages
  - The model detects path between crop rows which is then used by the vehicle to autonomously navigate

Figure 1. Red rover for autonomous navigation

Materials and Methods

Fully convolutional neural network for semantic segmentation

- Classifies each pixel in an image to a predefined class
- Consists of two parts; Convolution for detecting important features, and deconvolution to increase the spatial resolution of the features.

Model training

- More than 400 labelled image to indicate the path between cotton rows
- Training dataset (80%), validation set (10%), Testing set (10%)

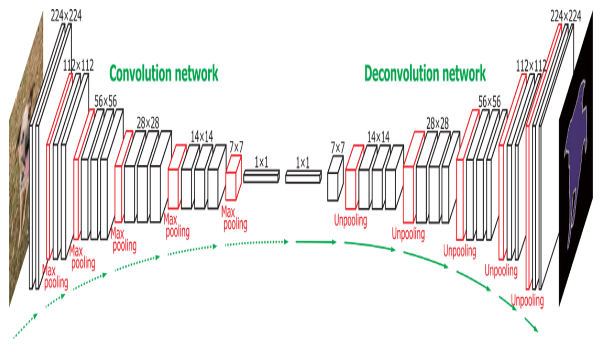

Figure 2. A fully convolutional neural network

Figure 3. Cotton rows and paths (**A**), Expected segmentation mask (**B**)

Rover navigation

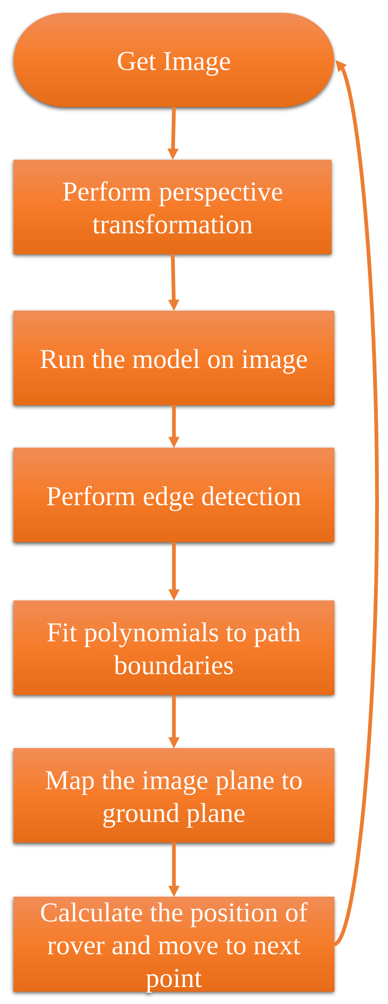

Figure 4. Context of the process to detect path and get rover position

Figure 5. Acquired image from the front camera (A) and the bird's eye view of the image (B)

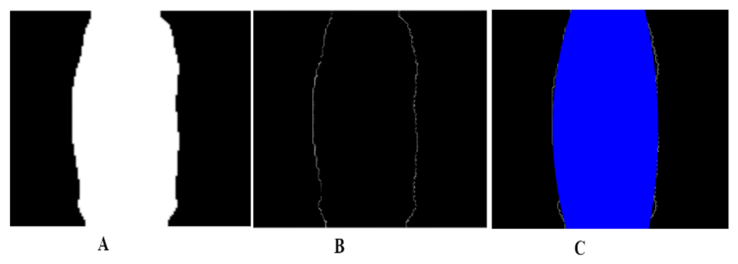

Figure 6. A segmentation mask of the transformed image (A), edge detection result on the segmentation mask (B), and polynomial fitted into left and right path boundaries to form a plane (C)

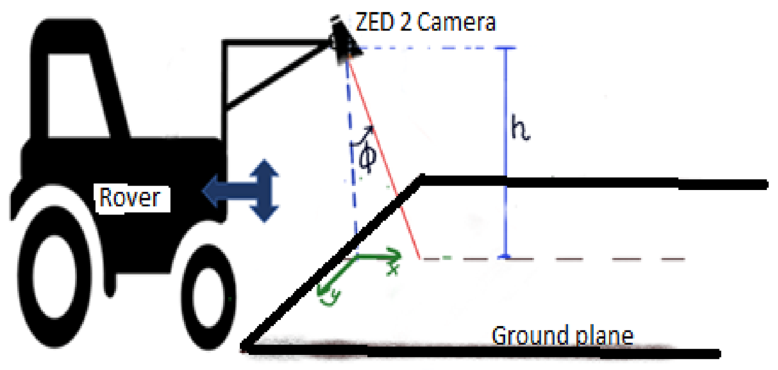

Figure 7. Camera setup and the ground plane coordinates

Experiment setup: Detecting a path in cotton field and determining the rover position

- Two (2) periods of growth stages (early and late)
- Rover navigating at 1mph
- Eight (8) 30-feet plots per stage
- Position data recorded in 1-feet intervals
- Three (3) different camera angles

Results

Semantic segmentation model

- Robust against different lighting conditions, shadows, cotton growth stages, weeds

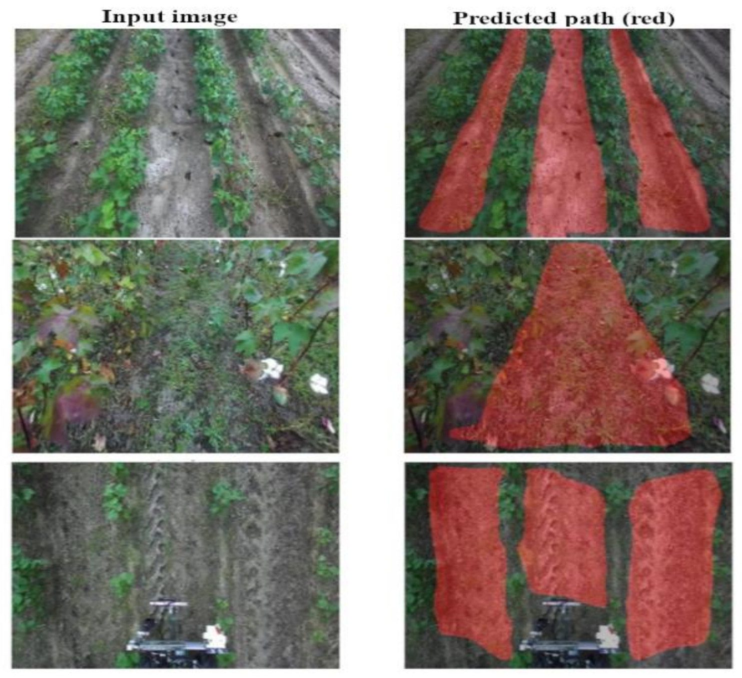

Figure 8. Examples of tested images on the FCN model and their predicted results

Rover navigation

Table 1. Error between reported position and real rover position

Field Condition	Mean error (m)	Standard deviation of error (m)
Early season	0.07	0.037
Late season	0.12	0.072

- Two-sample t-test showed no significant difference between the rover physical position and the predicted position
- There was no significant difference between the seasons position deviations

Figure 9. Predicted path and rover position for early season

Figure 10. Predicted path and rover position for late season

Hypothesis

Deep learning model can be used to detect paths between cotton rows to accomplish autonomous navigation in agricultural fields.

Objectives

- Training a deep learning segmentation model (U-Net) to segment paths from cotton rows in images
- Using the model to detect paths in images acquired from a rover camera and generate a 2D plane in image domain to represent the path
- Mapping the path from image plane to ground plane to get rover position and coordinates of the path for rover to navigate.

Conclusions and Discussion

Conclusions

- Fully convolutional neural network for semantic segmentation model proved to be an effective method of detecting paths between crop rows
- The model was robust against illumination, shadows, row discontinuities, camera angle, and cotton growth stages
- Mapping from image domain to ground plane was effective in determining the position of the rover which enabled it to navigate successfully
- Minor inconsistences were observed on paths which were extremely occluded by cotton leaves in late growth stages

Discussion

- More training examples will improve detection especially in late stages of growth
- Sensor fusion techniques can improve row following task (e.g., GPS fused with machine vision)
- The camera can also be used to avoid obstacles and ditches