Automatic Topological Mapping for Agricultural Robots

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Introduction

The deployment of fully autonomous mobile platforms to real-world farms is fast approaching, aiming to solve challenges from a growing population, labor shortage, and pressure to reduce environmental. First and foremost to this deployment is safe and precise navigation across the farm environment. This work presents **a novel approach to automatic topological map creation from aerial views of a field to guide the mobile robots along crop rows.**

Methodology

For our approach to automate deployment in new fields, a topological map is created by converting the captured aerial image into a set of waypoints, connected with traversable edges.

- First, we find the locations of crops by colour-based segmentation.
- We then determine the principal angle of parallel crop rows visible in the segmented binary image. We construct a set of oriented graphs (0 to 180°) resulting from the sum of intensities across interval lines perpendicular to the orientation (Fig. 1). The principal angle, α, is determined as perpendicular to the graph with the highest mean peak.

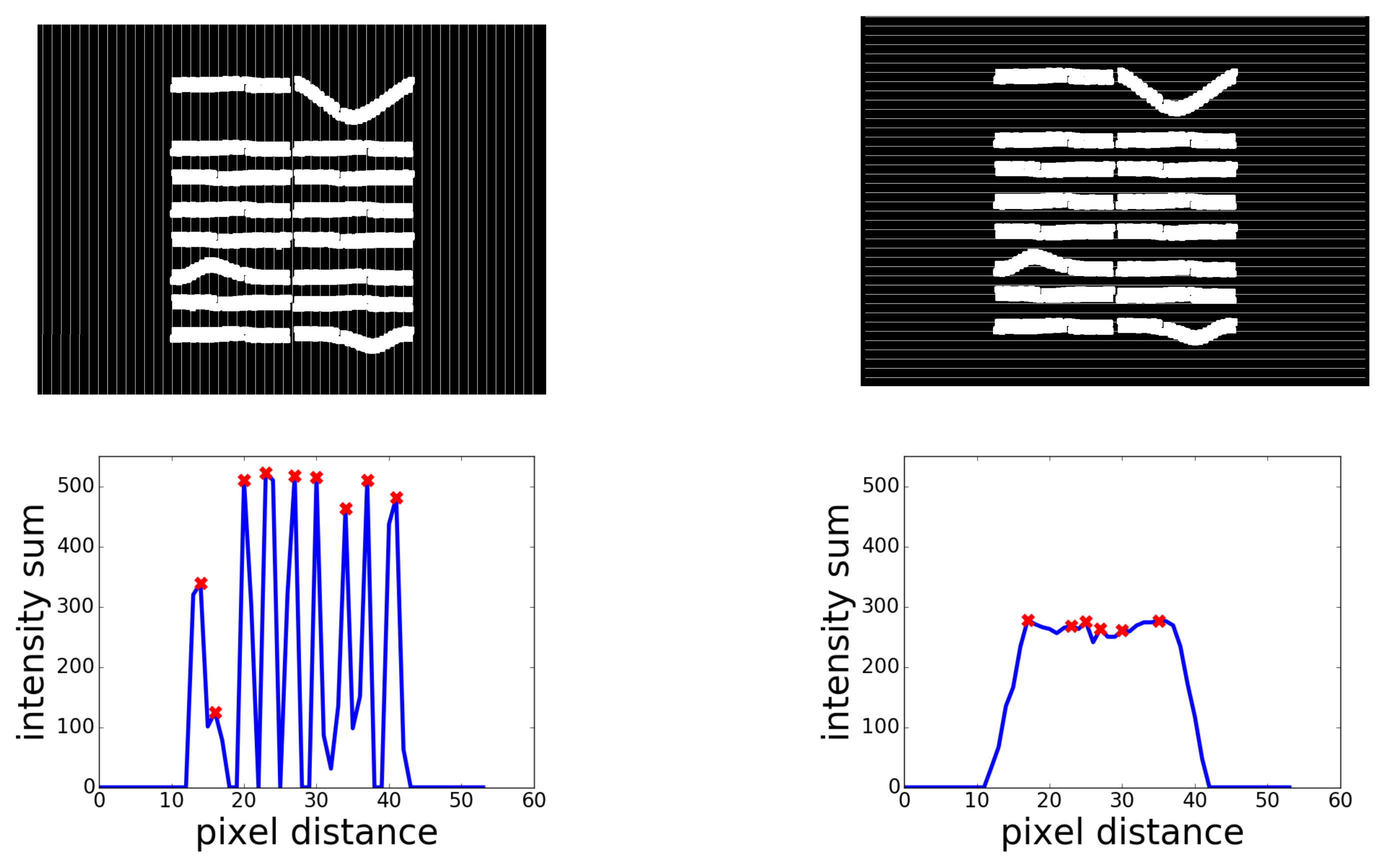

Fig. 1: Perpendicular lines drawn on the binary image at angle 0° (left) and 90° (right), along with their oriented graphs of intensity sums.

- Waypoints are then placed on the centre of crop clusters along the intensity profile lines perpendicular to the principal crop row direction α (Fig. 2, left).
- The waypoints are clustered into individual rows and ordered to produce a continuous safe route for travelling along each crop row. Safe turning points are appended to start and end of each crop row, parallel to α (Fig. 2, centre).
- Next, we remove redundant waypoints, for which the deviation from the previous direction of travel is only within some permitted perpendicular distance, ℓ. The result is a sparser set of relevant locations where the direction of travel changes by more than ℓ (Fig. 2, right).

This down-sampling procedure introduces a sparsity-accuracy trade-off and majorly influences the performance of the finished topological map. This trade-off is evaluated in the following.

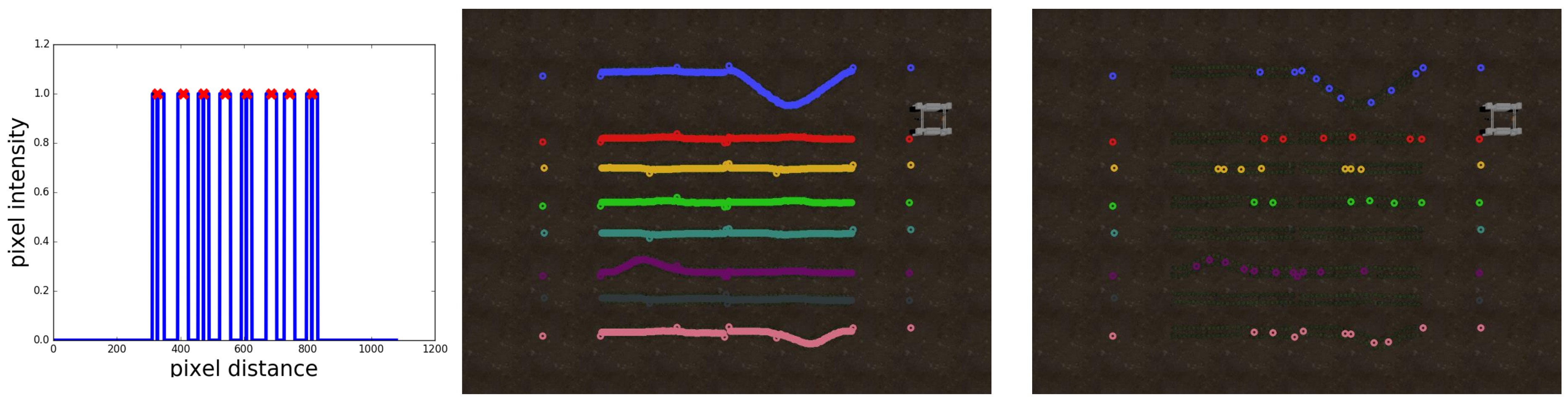

Fig. 2: Left: Placement of waypoints (red) on peak clusters, Centre: dense waypoints sorted into individual rows, Right: a sparse variant of the same topological map.

Evaluation & Results

We first evaluate our approach on a digital twin of a farm environment simulated in Gazebo[1], constructed with real images of soil and crops collected from the farm facilities of the University of Lincoln. This test scenario includes three regular fields with different row crops (basil, lettuce, and onions), and one set of non-uniform rows with gentle and severe bends simulating situations where there are environmental obstacles present in the field (for example see Fig. 3).

Coverage is measured as the proportion of the area in which crops grow (as manually annotated), that has successfully been surveyed by a simulated Thorvald robot[2] travelling along the generated topological maps (Fig. 4).

Fig. 3: Digital twin environment with bends

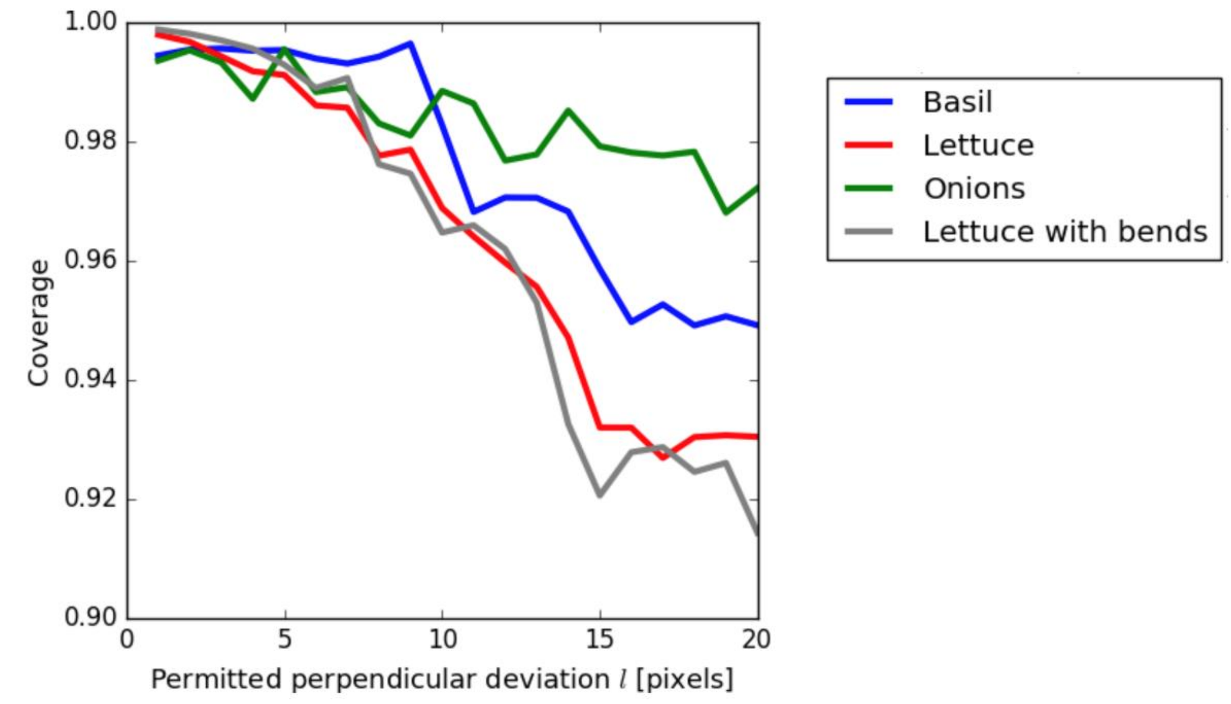

Fig. 4: Coverage in four scenarios dependent on the maximum permitted perpendicular deviation ℓ from previous travel direction.

We also applied the method to an aerial image taken by UAV of a real a Lincolnshire farm[3] growing winter wheat for validation of our approach (Fig. 5).

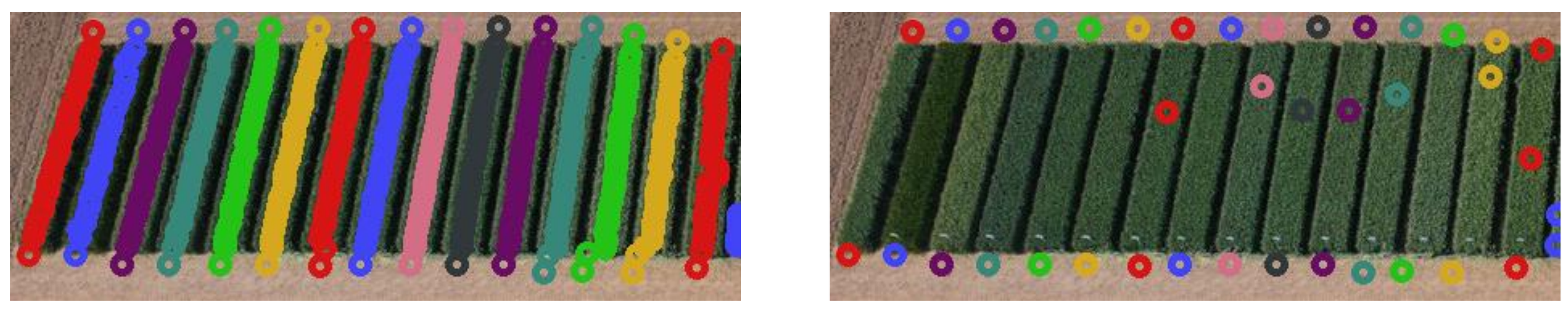

Fig. 5: Dense (left) and sparse (right) topological map generated from an aerial image of a real farm of wheat crops.

Limitations become apparent when the algorithm is applied to a larger, more irregularly shaped field, in which the general direction of crop rows changes significantly (Fig. 6). The principle crop row angle found across the entire image is only suitable for part of the image. The algorithm fails to pick up on the crop rows on the left side.

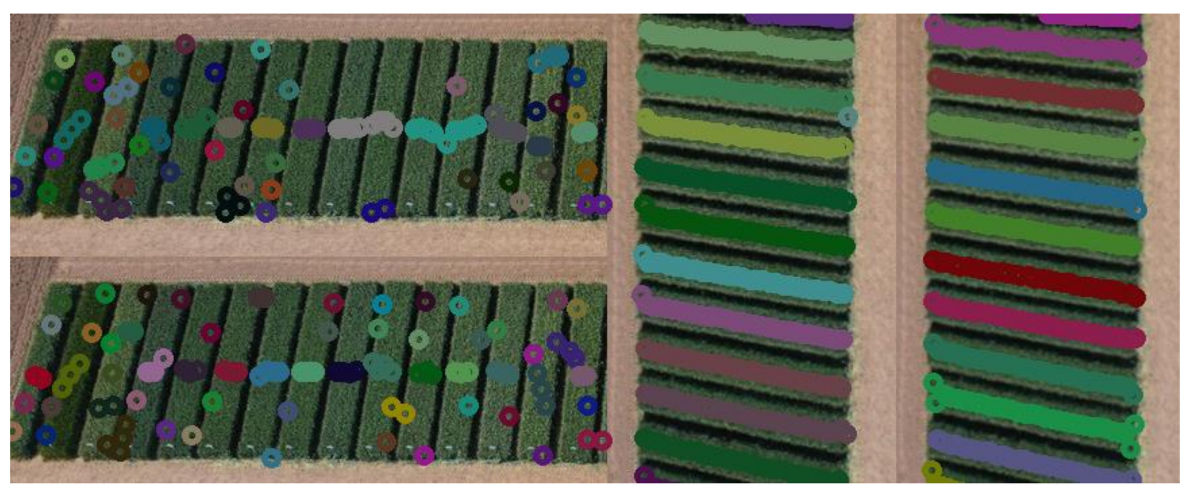

Fig. 6: The algorithm applied to a real-world scenario with changes in crop row direction.

Discussion

The proposed algorithm is robust to variability in crop placement and curvature within crop rows, and also translates well to real-world images (Fig. 5). To combat problems with large fields (e.g. Fig. 6), we propose to apply the algorithm in a hierarchical quadtree procedure, repeatedly partitioning the image and dynamically increasing the resolution in uncertain areas, thus evaluating the principal angles accurately for subsections of the field. In future work this system should be extended to create complete semantic maps of entire farm environments, enabling efficient automated fleet deployment for the next generation of agricultural robots.

References

[1] N. Koenig and A. Howard, “Design and use paradigms for gazebo, an open-source multi-robot simulator,” in *IEEE/RSJ International Conference on Intelligent Robots and Systems*, Sendai, Japan, Sep 2004, pp.2149–2154

[2] L. Grimstad and P. J. From, “The Thorvald II Agricultural RoboticSystem,” *Robotics*, vol. 6, no. 4, 2017

[3] Courtesy of Jonathan Trotter and SAGA Robotics