Automated Topological Mapping for Agricultural Robots

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***Abstract*—Essential to agricultural robot deployment in farms are accurate topological maps, which are manually created in current systems. In this work we present a novel approach to automatically generate a topological map along crop rows from aerials images for the deployment of agricultural mobile robots. We evaluate our system in a digital twin of a farm environment using real-world textures and physical simulation, and also demonstrate its applicability to aerial images of a real farm.**

***Index Terms*—Agri-robotics, Topological mapping, Mobile Robot Navigation**

I. Introduction

The deployment of fully autonomous mobile platforms to real-world farms is fast approaching, aiming to solve challenges from a growing population, labour shortage, and pressure to reduce environmental impact [1]. The deployment of fully autonomous mobile platforms to real-world farms requires solving a range of technical challenges. First and foremost safe and precise navigation across the farm environment. In this work, we present a novel approach to automatic topological map creation from aerial views of a field to guide the mobile robots along crop rows.

Thanks to recent advances in mobile robotics, manipulation and computer vision, modern agricultural robots can be deployed in various agricultural environments and are able to complete tasks such as crop scouting, pest and weed control, or harvesting [2]. Automated mapping of farm and field environments is an essential stage towards their commercialisation [1]. Currently, predefined topological maps are used to navigate up and down crop rows to deliver crop treatments [3]. Farms are constantly changing, crop rows and farm structure will vary over time requiring new topological maps which are typically created manually [4]. Our proposed solution addresses that problem by automating the topological map creation. Although automated waypoint creation from a map is a well-studied problem, it has not been applied in agricultural applications. Current crop row segmentation algorithms often rely on assumptions of straight, parallel, equally spaced crop rows, using e.g. Hough transforms [5]. These perform well on straight rows but fail when the crop rows are curved, which often occurs in fields with trees, pylons or ditches, or when the crop rows change direction in irregularly shaped fields [6]. Current solutions also commonly use sensors positioned close to the ground and thus focus on local guidance [6], [7].

The key contributions of this paper are a novel method of crop row detection and topological mapping from aerial images, which takes into account common crop row variations found in fields and evaluation of the method on both real world fields and simulated digital twins.

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II. Methodology

The proposed approach uses aerial images of a farm, such as hi-resolution UAV or satellite images. In this work we use real images of a Lincolnshire farm captured by UAV, as well as a digital twin of a farm environment simulated in Gazebo [8]. The ground plane of this environment is covered with textures, consisting of real images of soil and rows of different types of crop, collected from a camera mounted on a mobile platform deployed at the real farm facilities of the University of Lincoln.

To avoid harm to the crop, mobile robots should travel across the field along the centre line of crop rows only. 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 in the image 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. A dense set of waypoints is then placed on the centre of crop clusters along the intensity profile lines perpendicular to the principal crop row direction a (Fig. 2, left). The waypoints are clustered into individual rows and ordered by their distance along each row, to produce a continuous safe route for travelling along each separate crop row. Additionally, a safe turning point is appended to the start and end of each crop row, parallel to α (Fig. 2, centre).

Next, we remove redundant waypoints from the dense set by omitting 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 containing only waypoints in 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

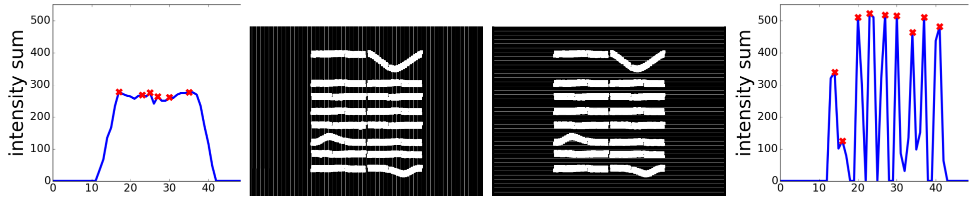

Fig. 1: Perpendicular lines drawn on the binary image at angle 0° (left) and 90° (right), along with their oriented graphs of intensity sums.

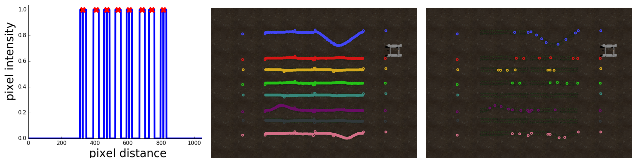

Fig. 2: Left: Placement of waypoints (red) on peak clusters, Centre: dense waypoints sorted into individual rows, Right: a sparse variant of the same topological map.

the performance of the finished topological map. This trade-off is evaluated in Sec. III.

III. Evaluation

A. Experimental Setup

The quality of the topological map was assessed by its coverage, measured as the proportion of the area in which crops grow (as manually annotated), that has successfully been surveyed by a simulated Thorvald robot [9] after it visited every way point on the topological map once. We report results for three test scenarios consisting of rectangular 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. Additionally, we also applied the method to an aerial image taken by UAV of a real Lincolnshire farm[1] (see Fig. 4 and Fig. 5) growing winter wheat for validation of our approach.

[1]courtesy of Jonathan Trotter and SAGA Robotics

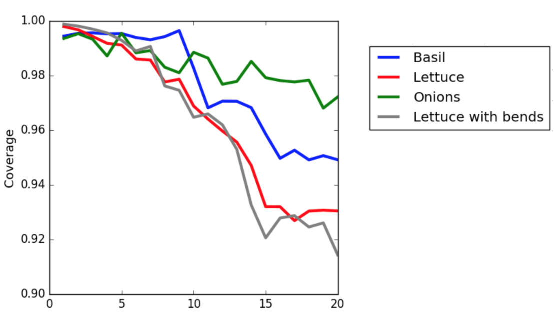

Fig. 3: Coverage in four scenarios dependent on the maximum permitted perpendicular deviation l from previous travel direction.

B. Results

The proposed algorithm deals well with variability in crop placement and curvature within crop rows. For straight crop rows (see Onions in Fig. 3), even very sparse maps achieve near optimal coverage. The approach also translates well to real-world images (Fig. 4). However our algorithm's 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. 5). 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.

IV. Conclusions and Future Work

We presented a novel topological mapping algorithm, which is robust to curvature within single crop rows. We also demonstrated its applicability to real-world examples. However, this algorithm is presented as a baseline for future development. To map large fields (Fig. 5), we propose to repeatedly 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.

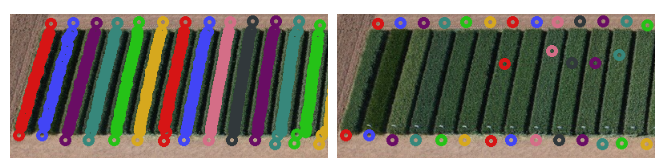

Fig. 4: Dense (left) and sparse (right) topological map generated from an aerial image of a real farm of wheat crops.

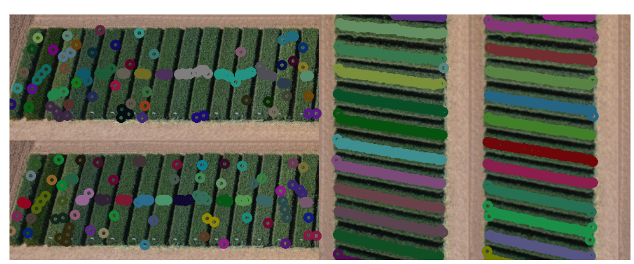

Fig. 5: The algorithm applied to a real world scenario with changes in crop row direction (Composite image).

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