Closing the Gaps in Crop Management: UAV-Guided Approach for Detecting and Estimating Targeted Gaps Among Corn Plants

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1. Introduction

Accurately identifying gaps within the crop field and filling them is a vital step in ensuring high crop yield [5, 17]. The conventional methods for detecting and filling the gaps manually require significant time and effort [4]. To the best of our knowledge, there is no standardized protocol for detecting gaps within the corn crop in terms of sensors and methods used. The methodology in this study integrates UAV-based imaging and computer vision algorithms for detecting corn plants, rows, and targeted gaps within the rows, to accurately assess plant population and identify gaps within the crop field [6, 7, 8, 12, 13, 14, 15, 16].

2. Methodology

We acquired 210 raw high-resolution RGB images of the experimental corn field in the village of Srbobran, Serbia, with the exact location of 45°34'25.9"N, 19°50'39.3"E, spanning an area of 0.53 acres with 21 corn-sowed rows. Images were captured in May 2021 with DJI Inspire 1 UAV equipped with a Zenmuse X3 camera [20] from a height of $15m$, during the V4 (4-leaf) growth stage. Within this stage corn plants developed four visible leaves and continue to grow rapidly, so that the leaves become more developed and structured. With the mission planning software UAV was set up to capture images at 75% frontal lap and 65% side lap which later resulted in a successfully created orthomosaic of size $5{,}795 \times 27{,}754$ with ground sampling distance (GSD) of $0.9cm$, using Pix4DMapper [10]. To establish ground truth data for plant population and gap analysis, a GPS location of every plant within the corn field was manually obtained using ArcGIS software [11]. As a result, $16{,}720$ plants were manually marked within the created RGB orthomosaic. Based on those marked plants we obtained the distances between each consecutive plant within a row. We further identified ground truth for 154 targeted gaps with a length $\geq 45cm$, which is the minimal length that provides potential space for reseeding additional plants [9]. The created RGB orthomosaic was subjected to a patch-based division, by incorporating an overlap of 20% between adjacent patches to ensure comprehensive ucoverage. Individual patches were created with dimensions of 240×240 pixels and are further used for gap detection and their length estimation. As a result, a total of 810 patches were generated.

For corn plant detection three methods are tested on whole corn field image (divided into 810 patches) as an initial step for gap detection: unsupervised based segmentation of the Visible Atmospherically Resistant Index (VARI) map, template matching (TM), and a deep learning model MaskRCNN [2, 3]. The VARI method uses an RGB image to generate a map on the basis of greenness, so green plants were detected by using a threshold of 0.6 for index value and an area value close to an average plant area at this stage (i.e., 0.4m^2 to 0.6m^2). In template matching [1], 5 templates of corn plants were randomly selected and a fast normalized cross-correlation technique [19] was applied to complete corn field. It was processed using a sliding search window and a threshold value of 0.5 with the aim to find instances of each of the templates in the image of corn field. Plant detection results were finalized by compiling together all of the plants detected by the templates. Furthermore, MaskR-CNN R50-FPN model from [18] is trained using two classes: corn plant and non-corn plant objects. The non-corn plant objects encompassed various elements such as weed plants, rocks, and machinery marks in the soil. Total 21 images out of 810 images were used for training purpose with total 588 masks for corn plant and 42 masks for non-corn objects. We used $4{,}000$ epochs with 2 images per batch, with the learning rate set at 0.00025. Following the training phase, the model performances were evaluated on a complete georeferenced orthomosaic, using a threshold of 0.7 to detect plants.

After the first detection stage is complete, in the second stage the rows were identified by linking centroids of detected plants to their nearest neighbors, while ensuring a maximum connection distance of less than the row gap, typically $75cm$. These resulting polylines, formed from the

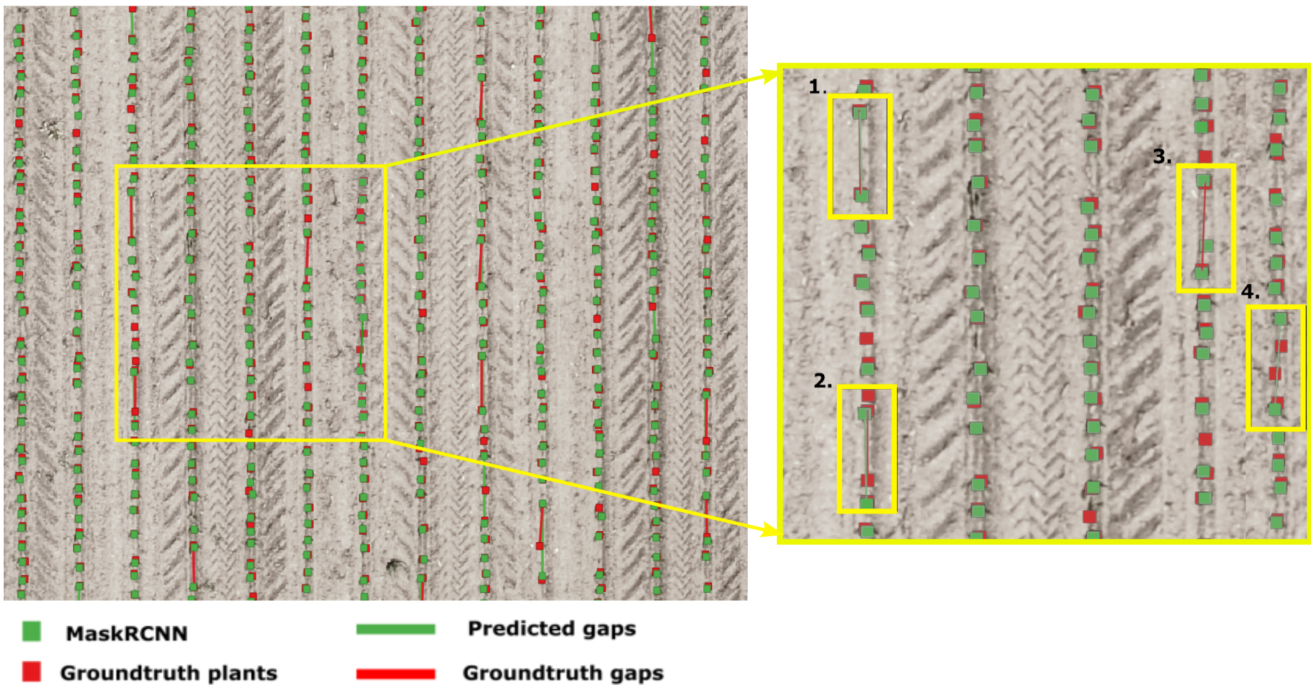

Figure 1. The impact of mis-detected plants on the gap length estimation in the overall detection compared to ground truth

vertices of plant centroids, were extended to intersect with neighboring polylines within the same row, facilitating the connection of sequential edges exclusively within the row. The outermost points of each row were then utilized to generate a continuous straight line, which serves to delineate the plants located within interrow spacing. Furthermore, these established row lines served the purpose of grouping plants within each row, enabling connections between centroids of adjacent plants solely within the same row. These connecting polylines, constructed using plant centroid vertices, represent the actual gaps between successive plants within the row. With detected polylines within each row, any polyline with a length exceeding the expected spacing between two corn plants ($\sim 45cm$) was identified as a targeted gap line. These lines served as a foundation for identifying specific areas within the corn field that required gap filling, indicating the available space for reseeding during the germination stage that enhance overall yield optimization.

3. Results

We used four metrics for a qualitative evaluation of the corn detection model: Accuracy, Recall, Precision, and F1-score, while for the qualitative evaluation of the proposed targeted gap detection, we used the mean square error (MSE) for the estimated length of correctly detected gaps.

From the presented results in Table 1, we can see that template matching detection and unsupervised segmentation of VARI index map showed much lower performances compared to MaskR-CNN R50-FPN model. Unsatisfactory results with these two methods are caused by falsely detecting weeds and grassland as corn plants. This misclassification undermines the reliability and usefulness of the VARI index map, as it fails to provide an accurate representation of the distribution and density of the corn plants. On the other hand, the main drawback of the template matching approach is the high-computational complexity, especially in scenarios where a comprehensive analysis of a large number of plants is required.

Table 1. Plant detection results of the competing methods

Metrics	VARI	TM	MaskRCNN
Accuracy	0.61	0.52	0.96
Recall	0.66	0.55	0.97
Precision	0.88	0.91	0.99
F1 score	0.76	0.69	0.98

In this part, we are focusing on 154 targeted gaps with at least $45cm$ in length. The average length of targeted gaps within the formed data set is $56cm$. The MaskR-CNN based model, as the best-performing model for plant detection, followed by a procedure for targeted gap detection, correctly detects 122 gaps. The MSE in estimating the length of those gaps is $1.4cm$. Figure 1 illustrates the influence of mis-detected plants on overall targeted gap length estimation error. Four distinct cases were observed: 1) correctly detected and accurately estimated gap length, 2) correctly detected gap with imprecise length, attributed to a mis-detected plant, 3) the gap was not detected due to a false positive detected plant, resulting in the omission of the existing gap, and 4) false positive detected gap arising from the prior detection's oversight of two plants. The observed instances of mis-detected gaps were primarily attributed to the failure in detecting plants during the prior detection stage. Consequently, in order to achieve satisfactory results in targeted gap detection, it is critical for the plant detection algorithm to exhibit the highest possible precision.

4. Conclusion

This study focused on the detection of targeted gaps in corn fields and their length estimation. The extracted information provides valuable insights for identifying areas in the corn field that required reseeding during the germination stage. Achieved results by the proposed method offer significant advantages over traditional methods, including improved accuracy and faster data acquisition.

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