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Corn planting quality assessment in very high-resolution RGB UAV imagery using Yolov5 and Python.

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Abstract. Uniform plant spacing along crop rows is a primary concern in maximising yield in precision agriculture, and research has shown that variation in this spacing uniformity has a detrimental effect on productive potential. This irregularity needs to be evaluated as early and efficiently as possible to facilitate effective decision-making. Traditionally, variation in seedling spacing is sampled manually on site, however recent technological developments have made it possible to refine, scale and automate this process. Using machine-learning (ML) object detection techniques, plants can be detected in very high-resolution RGB (red-green-blue) imagery acquired by an unmanned aerial vehicle (UAV), and after processing and geometric analysis of the results a measurement of the variability in intra-row plant distances can be obtained. This proposed technique is superior to traditional methods since the sampling can be made over more area in less time, and the results are more representative and objective. The main benefits are speed, accuracy and cost reduction. This work aims to demonstrate the feasibility of automatically assessing sowing quality in any number of images, using ML object detection and the Shapely Python library for geometrical analysis. The prototype model can detect 99.35% of corn plants in test data from the same field, but also detects 1.89% false positives. Our geometric analysis algorithm has been shown to be robust in finding planting rows orientation and inter-plant lines in test cases. The result is a coefficient of variation (CV) calculated per sample image, which can be visualised geographically to support decision-making.

Keywords. Precision agriculture, unmanned aerial vehicle, very high-resolution imagery, machine learning, sowing quality, corn.

1 Introduction

Over millennia, maize production has contributed to human community development (Brown and Darrah, 1985). Today it occupies the greatest share of the cereal production market, and many countries benefit from of this industry (Ritchie and Roser, 2020). Companies and whole countries are sustained by maize and its uses, including human and animal feeding (Rose et al, 2010) and bio-fuel production (Ranum et al, 2014).

In corn agronomy, several pivotal stages in the growing cycle exist where decision-making significantly affects the subsequent stage. Farmers take into account several planting quality considerations (Liu et al, 2004; Doerge et al, 2015), including sowing depth and inter- and intra-row spacing. Since the sowing process significantly influences the final plant stand emergence and therefore the yield, the sowing quality must be evaluated as early as possible for yield losses to be anticipated and for support decisions that could mitigate or help optimize resources while facing these negative effects, including strategies as variable rate fertilization (Shi et al 2013) or replanting (Terry et al, 2012).

Spatial distribution uniformity is measured by counting the number of plants in a certain distance within the row and the variability of their distances between each other. This variability in plant spacing is characterised by the Coefficient of Variation (Patel et al, 2001; Da Silveira et al, 2005; Storck et al, 2015) and is equal to the standard deviation divided by the mean, as in Eq. (1).

$$CV = \frac{\sigma}{\mu} \tag{1}$$

The CV is commonly measured manually in small portions of the field (Schmidt et al, 2001), selecting sampling sites arbitrarily. The process can be considerably time consuming, expensive, inaccurate and tedious, especially on extensive agricultural fields. Out of necessity, assessments and decisions are then based on these inherently non-representative samples (Kurachi et al, 1989). Due to this uncertainty, it is critical to minimise measurement errors and maximise measurement frequency.

Although several factors can have negative effects on plant development and yield (Martin et al, 2005), in general the literature suggests that irregular spacing is detrimental to crop performance (Easton, 1996; Hörbe et al, 2016; Kolling et al, 2016; Lauer and Rankin, 2004; Nielsen, 2004; Sangoi et al, 2012; Sgarbossa et al, 2018; Silva et al, 2015) and some authors have provided yield loss estimates as shown in Tab. 1.

Table 1. Estimates of corn yield loss due to plant-spacing variability.

Study	Yield loss per 10% increase in CV
	kg.ha-1
Easton, 1996	100
Hörbe et al, 2016	1,220
Sangoi et al, 2012	64 - 83
Kolling et al, 2016	65 - 187
Silva et al, 2015	282

Since the advent of computer vision and machine learning agriculture has experienced exponential growth in new technological applications (Lu and Young, 2020; Chang and Lin, 2018). Plant detection techniques for various vegetation types have been developed including segmentation (Junior et al, 2021; Shirzadifar et al, 2020), specifically using the excess green index (ExG) and Otsu's thresholding method (Li et al, 2019; Shrestha et al, 2004), deep learning with convolutional neural networks (CNN) (Fan et al, 2018; Zamboni et al, 2021; Li et al, 2016, Li et al, 2019), or a combination of these methods (Valente et al, 2020; Neupane et al, 2019; Jin et al, 2017). For corn fields, RGB data for early-stage plant stand validation is derived from manually transported sensors (Carreira et al, 2022; Easton, 1996), ground-based vehicle-mounted sensors (Jiang et al, 2015; Montalvo et al, 2012; Tang and Tian, 2008; Shrestha and Steward, 2003), and UAV-mounted sensors (Kumar et al, 2020).

In other studies, García-Martínez et al (2020) counted corn plants in drone imagery over tilled fields using image segmentation and cross-validation templates, resulting in high accuracy detection that decreased as the crop phenology advanced, while Karami et al (2020) also used CNN methods of segmentation along with morphological operations that needed to be set for each image analysed and reported trouble margining weeds. Osco et al (2021) detected plants and rows using CNNs with high accuracy in corn and citrus, however, the model was trained over tilled fields and had issues recognizing plants outside the rows. Ma et al (2021) sampled a corn field on a very advanced phenology state, with no major interference of weeds or background, they used CNNs for testing and combining different features including scale-awareness and channel interdependence and using visual geometry group network, obtaining high accuracy on the plant counting task.

The objective of this work is to demonstrate the feasibility of a combined machine-learning and geometry-based approach for planting quality assessment, and to provide a prototype implementation trained on corn crops.

2 Methodology

The workflow comprises two main parts: an initial object detection based on machine learning, followed by a geometric analysis of the identified objects. For the second part, a further division can be made between the cornrow-orientation determination method and the inter-plant spacing determination method.

2.1 Study Area and Data

Unmanned aerial vehicles (UAV) can provide very high-resolution imagery over comparatively large areas in a brief time. The images used in the study are from no-till management corn fields in eastern Paraguay and were taken by an DJI M300 drone using a H20 sensor at a relative altitude between 20 and 35 meters. The RGB pictures obtained have a spatial resolution of approximately 0.9 mm per pixel. With each image covering an area of between 10 and 20m^2 and with one image per hectare, sample imagery covers between 0.1 and 0.2% of the field. The images are JPEG-compressed with width 5184 and height 3888 (20 megapixels), with positional information recorded in XMP metadata.

2.2 Corn Plant Detection

Initially an image segmentation approach was taken, similar to the method of Shirzadifar et al (2020). A mask layer is obtained and stem locations can be approximated to object bounding-box centroids. This approach had significant difficulty with weeds, as well as in differentiating overlapping plants. Additionally, due to the sensitivity of the CV calculation, it was a requirement that the plant stem locations be detected more precisely.

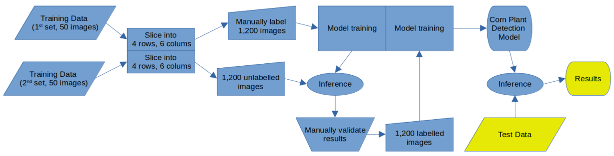

Figure 1. First phase workflow showing one manual and one semi-automatic training phase.

To develop an effective plant-detection model, the CNN-based single-stage object detector Yolov5 (Jocher et al, 2020) was used. For the training data set, fifty images were sliced into 24 smaller images each, yielding 1,200 images with a total of 2,727 manually labelled class instances. The region of interest (ROI) presented to the model consists of a small bounding box drawn around the centre of the corn plant. At the growth stage of interest, the plants exhibit a very prominent whorl. This small ROI allows partially obscured plants to be detected, since the Yolov5 model can infer obscured objects from context. These images were used to train a Yolov5l model for 100 epochs, with 10% randomly selected for validation. Peak Mean Average Precision at 50% confidence (mAP@.5) was reached at the 23rd epoch (0.941) and overfitting occurred thereafter.

This initial model was then used to detect plants in a second batch of 1,200 sliced images, and the inference results were manually corrected to produce another set of training data with 3,557 class instances. Using the first model's best weights and this set of training data (all other training parameters unchanged), after another 100 epochs a mAP@.5 of 0.984 was achieved. Active learning can be implemented by continued training with manually validated inference results. The worflow is shown in Fig. 1.

2.3 Crop row orientation

An iterative approach was used to estimate the crop row orientation. The locations of the detected plants are considered as a point cloud and lines of orientation 0° through 170° are successively plotted through the centre of the image in steps of 5°, clockwise from vertical. The distribution of the perpendicular distances from each point to this line is analysed to find the most densely clustered scenario, which occurs when the plotted line fits the crop row orientation most closely. The process is then repeated in the –5 to +5 range around the orientation of the line of best fit, in steps of 1°, to refine the result to within 1° of the true orientation of the corn rows.

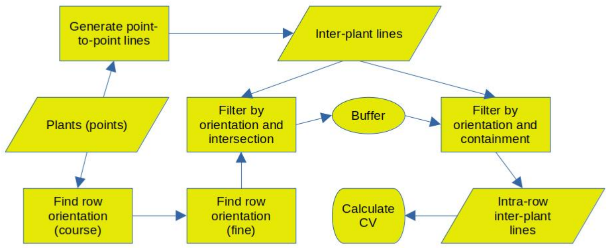

Figure 2. Second phase workflow consisting of automated geometric analysis.

For analysing the distributions of the perpendicular distances in the abovementioned steps, they are plotted in a histogram with 40 bins (Fig. 4). A discreteness index (DI) is then calculated as the product of the number of empty bins and the mean value of non-empty bins Eq. (2). The orientation of the line with the highest data discreteness index is taken as the orientation of the crop rows (θ).

$$DI = (Empty\ bins) \cdot \left(\frac{Plants}{Non-empty\ bins} \right) \qquad (2)$$

When finding the row orientation, test results show a single prominent peak in discreteness when the target angle is plotted (Fig. 3). Fig. 4 shows a comparison of the histograms for the target angle and an arbitrary incorrect angle. Here the clustering in distance values is evident as the angle approaches the true angle.

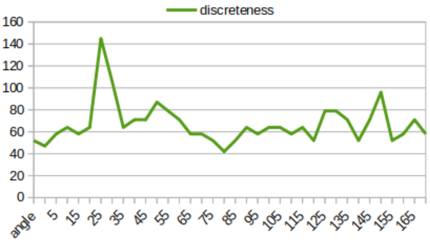

Figure 3. Discreteness index as it varies with slope.

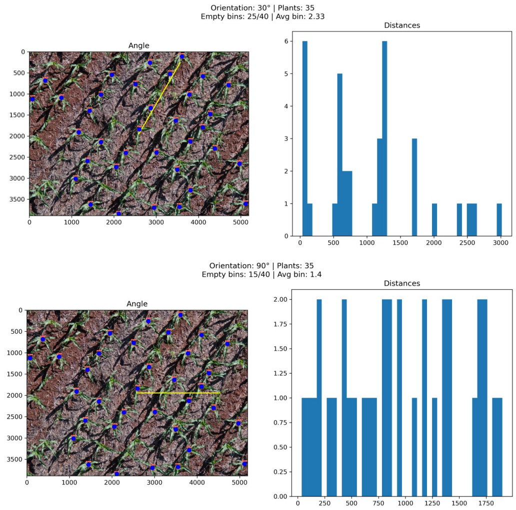

Figure 4. Histograms for orientation 30° and 90°, with discreteness indices 145 and 52.

2.4 Plant spacing measurement

Due to irregular plant emergence, lines are obtained in two phases. The first, strict phase finds whole crop rows, with a vertex at the first and last plant per row. All point-to-point lines are plotted and filtered by a threshold deviation from plant row orientation θ (Fig. 2). For the rows, this threshold is comparatively small as they are expected to be regular over any moderately extensive distance. The resulting subset of lines is run through an iterative filter where the shortest of any pair of intersecting lines is discarded. Eventually only the longest lines per row remain and a buffer is constructed around them to be used in the next phase.

The second, more lenient phase filters the lines by a much higher deviation threshold, to account for plants that are significantly offset from the centre of the corn row (up to 20° deviation from orientation θ). The resulting lines are then filtered by whether they are within the buffered corn rows and contain only two plants (start and end vertices) within their own buffer (Fig. 2). The result is a collection of lines representing the inter-plant distances along the crop rows for all the rows that could be discerned from the input data.

The dimensionless target metric, the inter-plant spacing Coefficient of Variation (CV), is then given by the standard deviation of the distances divided by the mean.

2.5 Data and Software Availability

Scripts are available on GitHub at https://github.com/lucasuccio92/plantycs.

3 Results

Crop detection performance is expected to improve with increased learning, but the second-generation model already shows 98.4% mean average precision at 50% confidence. In practice, the results have varied depending on the growth stage of the corn. Detection results from 10 test images show that the model can detect 99.35% of plants with 1.89% false positives in test cases at the same growth stage (Tab. 2). 20 test images from a slightly younger crop showed less accurate detection, due to the undeveloped whorl in immature plants.

Table 2. Method accuracy and errors in 30 test images at two different growth stages.

	Same crop	Younger crop
Omission Error	0.65%	8.13%
Commission Error	1.89%	3.42%
Row Orientation Detection Accuracy	100%	95%
Row Detection Accuracy	99.23%	96.72%
Inter-plant Space Detection Accuracy	95.70%	94.39%

Most false positives consist of large weed grasses similar in appearance to emerging corn. Approximately 40% of missed detections are caused by the leaves of neighbouring plants obscuring the centre of the corn crop. An exceedingly small percentage of error (0.0026%) derives from the model identifying two corn centres where only one exists (Fig. 5). This problem can be mitigated by flagging instances where two plants are detected in very close proximity, allowing manual or automatic rule-based correction.

Figure 5. Detection results showing confidence (zoomed in image). False positives can be screened by adjusting the threshold confidence.

The image-size parameter is an important consideration when using the model for inference on high-resolution imagery. In 41 test images, the number of plants detected increased with every increase in the image-size parameter, as it specifies the width to which input images are resized before being presented to the model for inference. With increasing resolution presented to the model, smaller objects become identifiable. Predictably there is a computational cost incurred with every increment in this parameter (Tab. 3).

Table 3. Detection results using different image-size parameter values.

Image-size	Plants detected	Pre-process time	Inference time
		ms	ms
640	791	1.8	508.8
864	1,796	1.4	1,019.6
960	2,050	1.7	1,147.8
1280	2,426	6.6	2,220.4
1920	2,636	8.3	3,438.6
3840	2,715	32.1	14,298.2

The detection model has been tested for robustness against noise. Motion blur is a common concern in aerial photography and the severity of distortion directly affects model performance. The following images (Fig. 6) show degrading detectability with increasing linear motion blur.

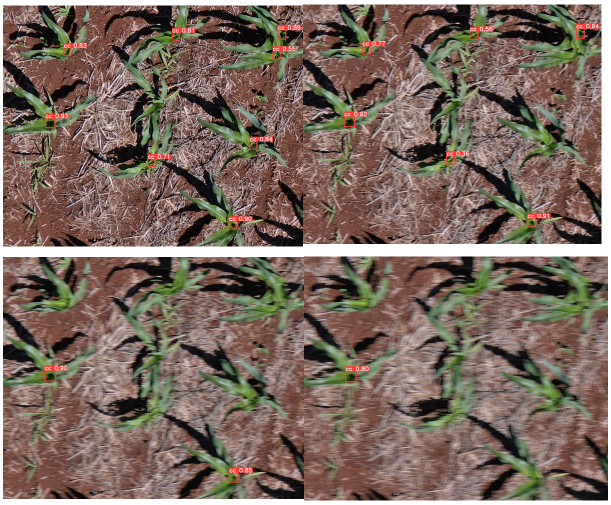

Figure 6. Detection failure due to motion blur (0-, 10-, 20- and 30-pixel linear motion blur).

Fig. 7 shows the final per-sample result. On the input image, the corn plants have been marked, the crop rows inferred and plotted and the intra-row plant spacing is shown. The CV calculated in this instance is 23.05%. Results for multiple images are returned as a geometry collection and can be visualised as in Fig. 8.

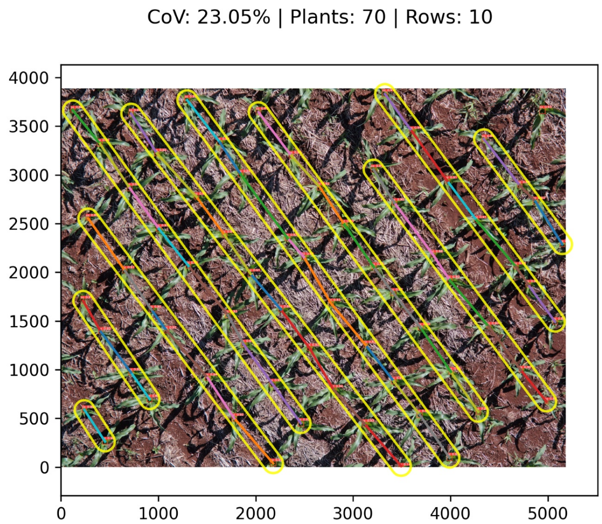

Figure 7. Processed sample showing rows, inter-plant spaces and CV

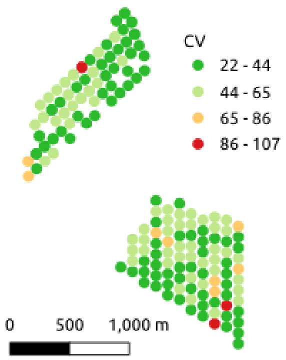

Figure 8. Map of sampling results from a single field.

A final evaluation was conducted to test the reliability of the proposed method. The CVs in 10 automatically detected and analysed samples were compared to the CVs after manually correcting the same samples. The result was a Mean Absolute Error of 4.86.

4 Discussion

Our results compare favourably with Shirzadifar et al (2020) who achieved 91% accuracy using segmentation and k-means clustering in a tilled field. Since our methodology requires no pre-processing or segmentation, the process is more direct in principle. Masks were not used to marginalize the plants from the rest, as can be seen in other literature reviewed, where the implementation of ExG, Otsu's, k-means and two-dimensional matrix (Shirzadifar et al. 2020), Hough transformation, U-Net binarizations (Kitano et al. 2019, Vong et al 2021) and combination of these (García-Santillán et al. 2018, Montalvo et al. 2012, Zhang et al. 2018) are critical for obtaining accurate results in counting, row detection and within-row distribution uniformity measurements in no-till conditions. Although these proved to be valid, some methods rely heavily on no-interference conditions in tilled fields or even relied on simulated corn fields. Weeds and residues are commonly present in no-till extensive agricultural fields and can pose a major challenge to AI-based plant detection techniques.

Results presented by Velumani et al. (2021) showed high accuracy in plant detection in early stages using Faster R-CNN, without segmentations or masks in very high-resolution images and using bounding boxes that covered whole plants, however these experiments were carried over tilled fields. Our detection method has proven robust against closely spaced and overlapping plants and, most remarkably, against no-till field conditions containing residues and weeds. Due to the small ROI, the model can precisely detect partially visible plants. This is an improvement over blob-based segmentation methods like Vong et al (2021) and Shirzadifar et al (2020) where overlapping plants and weeds present difficulties.

For making a proper ROI selection it was important that the images were taken between v3 and v5 stage of corn phenology and 25 days after sowing (DAS), since most plants are expected to emerge by that time, reducing false negatives and having a broader variety of plants that did not escape the detection algorithm due to their size heterogeneity. Similar stages were considered by Shirzadifar et al (2020) and Zhang et al (2018). Further stages such as the ones presented by Kitano et al (2019) were also valid but can reduce the action margin and proved to decrease the accuracy of the model due to the plants' development, a small number of plants are undetected due to partial or complete obscurement by a neighbouring plant. Vong et al (2021) performed their study 15 DAS when, in regular field conditions, there might still be plants that would not have completely emerged to be detectable.

The row-orientation algorithm is susceptible to highly regularly spaced (lattice-like) planting and can fail in cases where plants are nearly symmetrical in more than one direction. This problem can be partly offset by parameter adjustment. Another issue arises where different rows meet in a single image, due to turning or re-entry manoeuvres by the sowing machine. Samples without a dominant row orientation can be ignored by specifying a minimum deviation from the mean or calculating a confidence index. A further consideration is the orientation threshold for inter-plant distance lines, which can deviate extremely from the orientation of the row. To ensure that such lines are not filtered, the tolerance parameter can be adjusted accordingly.

A clearer visualization of planting quality assessments in addition to its spatial referencing availability, can provide a substantial possibility to improve and scale practices, potentially benefitting many parties involved in maize production.

5 Conclusions

Our method addresses difficulties that the high granularity of the imagery might pose for traditional segmentation-based plant detection in no-till fields, such as the presence of residues and weeds which may interfere with or confuse the detection model. An object-detection approach appears to be more suitable for uncontrolled field conditions.

This process can be extended to other crops, requiring only that the detection model be trained on the relevant data. Using relative altitude and sensor specifications embedded in image metadata, it is possible to calculate the ground sampling distance (GSD) and derive other relevant metrics from the samples, such as plant density or actual plant spacing. Similarly, the process can be extended to wider area images to achieve greater sampling coverage.

Apart from instances where the model fails to adequately detect plants prior to the distance uniformity evaluation, our method still manages to deliver more robust information compared to the traditional approach. It is also superior in terms of reliability and area surveyed in relation to labour time. The validity of the final CV calculation depends on the accuracy of the detection. Thus, reliability can be improved by continuous detection model training.

Very high-resolution UAV imagery and artificial intelligence techniques can improve upon traditional methods by measuring the same metrics over more area in less time. The result obtained with our method is also transparent and robust, resulting in clear and non-biased data to support management decisions.

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