Project Report:

In-field soybean seed pod analysis on harvest stocks using 3D imaging and machine learning

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To characterize the phenotypical traits of soybean seed pods, this study uses a stereoscopic sensing technology to obtain three-dimensional data of soybean plants before harvest. However, soybean seed pods grow in different directions and in clusters, it is difficult to analyze them from the images of only one side of crop rows due to occlusions. To that end we designed a gate-shaped camera rig to mount our PhenoStereo 3D cameras on both sides of the gate to capture soybean images from two sides (Figures 1 and 2). A caster wheel on the side further away from the Phenobot body was used to allow the rig rotatable along with the robot body and a rotational hinge at the rear of the Phenobot was employed to accommodate the unevenness of the soil surfaces. In our experimental field, the height of most soybean plants was less than 40 inches, therefore the height of the rig was designed to be 40 inches. Since the row spacing of the soybean plants is 30 inches, the width of the camera rig was designed to be 30 inches as well.

Figure 1. CAD model of the gate-shaped camera rig mounted at the rear of the Phenobot.

Figure 2. Field imaging of soybean pods using PhenoStereos and PhenoBot.

For data acquisition, four customized PhenoStereo cameras that consists of two FLIR BFS-U3-50S5C-C cameras each with customized data acquisition software were used to collect images of soybean harvest stocks. The lower two PhenoStereo cameras were used to capture most part of the sideview of the soybean plants, and the upper two cameras were used to capture images of the top part of those tall soybean plants. The raw images have a resolution of 2448 $\times$2048 pixels and were captured at 10 FPS at a travel speed about 2 mph. The shutter speed was set to 0.3 ms. The Soybean images were collected in the field at Agricultural Engineering and Agronomy Research Farm in Boone, Iowa.

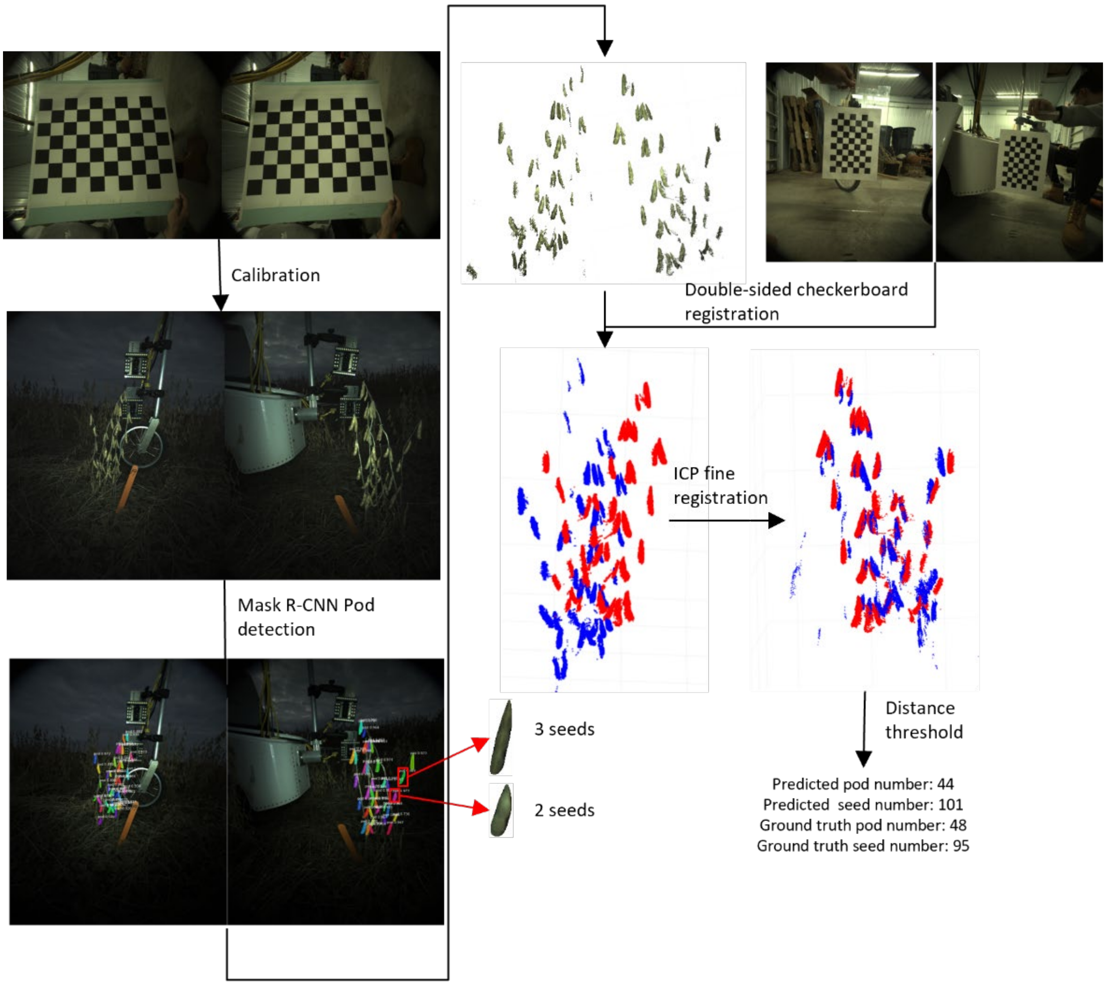


Figure 3. The flowchart of the proposed soybean seed pod counting method.

The flowchart of the proposed soybean seed pod counting method is shown in Figure 3. Firstly, some pictures of the checkerboard were collected to calibrate the cameras. A deep learning detection method called Mask R-CNN was used to detect individual soybean pods in the images from two sides of soybean plants. After segmenting pods in the images, each pod was transformed into 3D space. Some pods can be captured from cameras at both the left and right sides. To identify those pods, we reconstructed the soybean pods into 3D space. The detected pods were converted to point cloud based on the camera parameters. Because the point cloud of the pods distributed on the two sides of soybean rows was captured by the two stereo cameras facing each other, they need to be registered. To register the point cloud from the facing cameras, we made a double-sided checkerboard to match the same point captured from different views. The ICP algorithm, a common method for point cloud registration, was adapted then to conduct point cloud fine registration. After trial-and-error process, the RMS difference and final overlapping rate parameters of the ICP algorithm were set to 1.0E-05 and 90% respectively to produce a satisfactory registration result. To merge the same pods captured from two views, a distance threshold was used. If the distance between two pods in different views is too close, they were considered as the same pod. We obtained the pod number after identifying the pods that were counted twice and subtracting their number from the total. To evaluate the proposed method, we chose six thresholds, which are 5mm, 10mm, 15mm, 20mm, 25mm, and 30mm. In the evaluation, three soybean plants were chosen to test the performance of the proposed method. The counting error was defined as the mean absolute percentage error (MAPE) of the selected test samples. Table 1 shows the counting error of different distance thresholds using images captured from both sides of the soybean rows. Both MAPE and R-square of pod counting show that 20mm produced the best results. When compared with the counting accuracy using only one side images, the MAPE of pod counting decreased from 20.12% to 11.91% while the R-square value increased from 0.82 to 0.92.

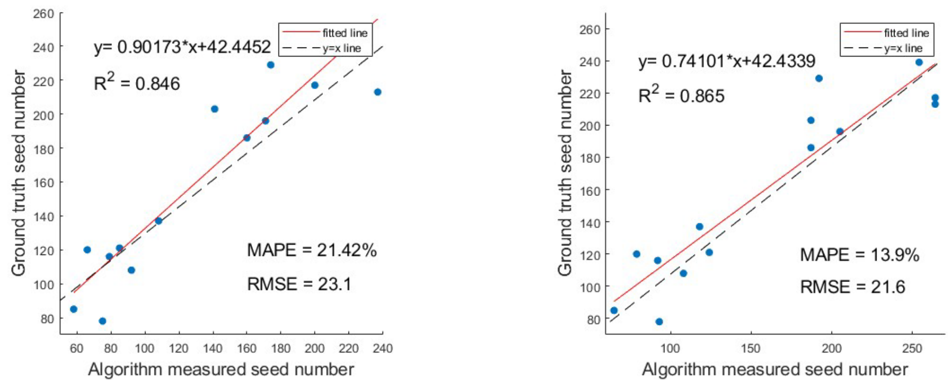
Table 1. Counting error under different distance thresholds

Parameter	**MAPE**	**R-square**
5mm	35.40%	0.85
10mm	19.31%	0.86
15mm	13.97%	0.89
20mm	**11.91%**	**0.92**
25mm	13.33%	0.90
30mm	13.35%	0.91

After identifying all the individual pods, a deep learning-based seed recognition model was used to find how many seeds in each pod to calculate the total number of seeds grown on the soybean. To create the dataset to train the seed classification model, soybean pods were cropped from the images. The dataset consists of 1635 images. The distribution of the training set, validation set and test set in the dataset was 0.6, 0.2 and 0.2. The classification accuracies of 2-seeded and 3-seeded pods are shown in Figure 4 where74.0% of the 2-seeded pods and 69.6% of the 4-seeded pods. The overall classification accuracy is 71.9%. The confusion of the classification was mainly caused by the image quality. Using cameras with a higher resolution would help to increase the classification accuracy.

Figure 4. The confusion matrix of the classification model to identify the 2-seeded and 3-seeded pods.

The comparison of the seed counting accuracies using images captured from one side and two sides is shown in Figure 5. There were 14 soybean plant samples used to evaluate the accuracy of seed counting. This figure shows that using images captured from two sides of the soybean plant has lower MAPE, RMSE, and a higher R-square values.



(a) Seed counting using images captured from one side of the soybean plants

(b) Seed counting using images captured from two sides of the soybean plants

Figure 5. Comparison of seed counting accuracy between using images captured from one side or two sides.

In this project, we proposed an automated soybean seed and pod counting system consisting of a robotic platform and a set of deep learning based 3D point cloud processing algorithms for high throughput operations using images captured from two sides of the soybean plant. The results demonstrate that the proposed soybean pod and seed counting methods produced better accuracies than counting them using images captured from only one side of soybean rows. The proposed system can greatly reduce human effort. In the future, the counting and classification accuracies of the proposed system can be further improved by using more image samples to train the deep learning model as some highly overlapping pods were not detected. Besides, the accuracy of pod identification could be improved by combining multiple features like distance, inclination angle. Also, when there were overexposures, the quality of images was decreased, causing degraded 3D reconstruction. Improving the illumination uniformity of the strobe lights will alleviate this problem.

We presented our work on this project at the 2022 and 2023 ASABE conferences.

1. Liu, X., L. Xiang, L. Tang. 2022. In-field soybean seed pod phenotyping on harvest stocks using 3D imaging and deep learning. 2022 ASABE Annual International Meeting. Houston, TX, July 17-20, 2022. Paper No. 2201222.
2. Liu, X., L. Xiang, L. Tang, A. Raj, N. Butler. 2023. In-field soybean seed pod phenotyping on harvest stocks using 3D imaging and deep learning. 2023 ASABE Annual International Meeting. Omaha, NL. July 9-12, 2023. Paper No. 2301517.