High-Throughput Dynamic Monitoring Method for Field Maize Seedlings Postprint

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Abstract

Currently, dynamic detection and monitoring of corn seedling emergence mainly relies on manual observation, which is time-consuming, labor-intensive, and can only estimate overall emergence conditions using small quadrats. To address the inaccuracy issues in manual seedling dynamic management and achieve refined field management, this study constructed an image dataset of the corn seedling emergence process under different illumination conditions using two data sources: high-temporal-resolution visible light images acquired by a field crop phenotyping high-throughput acquisition platform and visible light images acquired by a UAV platform. Considering factors such as complex environmental backgrounds and uneven illumination in field conditions, residual units were constructed based on the traditional Faster R-CNN, and ResNet50 was employed as a novel feature extraction network to optimize Faster R-CNN, first achieving recognition and counting of corn seedlings in complex field environments; furthermore, based on the high-temporal-resolution image data acquired by the phenotyping platform, continuous monitoring of seedling emergence dynamics was conducted for corn plants of different varieties and densities, and evaluation and analysis of seedling emergence duration and uniformity were performed for each corn variety. Experimental results demonstrated that when the proposed method was applied to seedling emergence detection using the field crop high-throughput phenotyping platform, the recognition accuracies were 95.67% and 91.36% under sunny and cloudy conditions, respectively; when applied to the UAV platform, the recognition accuracies were 91.43% and 89.77% under sunny and cloudy conditions, respectively, which can satisfy the requirements for automatic detection of corn seedling emergence in practical application scenarios. Leveraging the advantage of the phenotyping platform in acquiring temporal data, further analysis of dynamic corn seedling emergence detection was conducted. The results indicated that the dynamic seedling emergence results obtained using this model were consistent with manual observations, demonstrating that the proposed model possesses robustness and generalization

capability.

Full Text

High-Throughput Dynamic Monitoring Method of Field Maize Seedling

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Abstract

At present, the dynamic detection and monitoring of maize seedling mainly rely on manual observation, which is time-consuming and laborious, and only small quadrats can be selected to estimate the overall emergence situation. In this research, two kinds of data sources—the high-time-series RGB images obtained by the plant high-throughput phenotyping platform (HTPP) and the RGB images obtained by the unmanned aerial vehicle (UAV) platform—were used to construct the image dataset of maize seedling process under different light conditions. Considering the complex background and uneven illumination in the field environment, a residual unit based on the Faster R-CNN was built and ResNet50 was used as a new feature extraction network to optimize Faster R-CNN to realize the detection and counting of maize seedlings in complex field environments. Then, based on the high time-series image data obtained by the HTPP, dynamic continuous monitoring of maize seedlings of different varieties and densities was carried out, and the seedling duration and uniformity of each maize variety were evaluated and analyzed. The experimental results showed that the recognition accuracy of the proposed method was 95.67% on sunny days and 91.36% on cloudy days when applied to the phenotypic platform in the field. When applied to the UAV platform to monitor maize emergence, the recognition accuracy was 91.43% and 89.77% on sunny and cloudy days, respectively. The detection accuracy of the phenotyping platform images was higher, which could meet the needs of automatic detection of maize emergence in actual application scenarios. To further verify the robustness and generalization of the model, HTPP was used to obtain time series data, and the dynamic emergence of maize was analyzed. The results showed that the dynamic emergence results obtained by HTPP were consistent with manual observation results, demonstrating that the model proposed in this research is robust and generalizable.

Keywords: field maize; Faster R-CNN; recognition; counting; dynamic seedling detection

1. Introduction

The dynamic monitoring of maize seedling emergence is critical for precision agriculture, yet traditional manual observation methods are labor-intensive and limited to small sample areas. Recent advances in high-throughput phenotyping platforms and unmanned aerial vehicles offer new opportunities for automated, large-scale crop monitoring. This study presents a deep learning-based approach using optimized Faster R-CNN architecture to detect and count maize seedlings under varying field conditions.

2. Materials and Methods

2.1 Data Collection Platforms Two distinct imaging platforms were employed to capture maize seedling data across different spatial and temporal scales. The Plant High-Throughput Phenotyping Platform (HTPP) provided high-temporal-resolution RGB imagery, while a UAV platform equipped with a SONY-5100 camera and 20mm lens captured aerial observations at 5280$×$3956 pixel resolution. The experimental site was located at 116°16 N, 39°56 E, with planting densities of 25,000, 40,000, and 55,000 plants per hectare.

[Figure 1: see original paper] Image collection using UAV
[Figure 2: see original paper] Schematic diagram of maize planting in the coverage area of HTPP
[Figure 3: see original paper] Field crop high-throughput phenotyping platform image acquisition device

2.2 Dataset Construction The dataset comprised images from both platforms under varying illumination conditions. Data preprocessing involved normalization and augmentation to address the challenges of complex field backgrounds and uneven lighting. The HTPP system captured images at 2048$\times 2048 pixelresolution, whileUAVimageswereprocessedinto 960 \times$960 pixel patches for analysis.

[Figure 4: see original paper] Data preprocessing flowchart of UAV and HTPP platforms

2.3 Model Architecture An optimized Faster R-CNN framework was developed using ResNet50 as the backbone feature extraction network, replacing the conventional VGG architecture. This modification introduced residual learning capabilities to better handle the fine-grained features of maize seedlings. The network architecture included a Region Proposal Network (RPN) with Non-Maximum Suppression for candidate region generation and ROI pooling for feature aggregation.

[Figure 5: see original paper] RGB images and their labels under different light conditions

[Figure 6: see original paper] Seedling detection process using Faster R-CNN
[Figure 7: see original paper] Faster R-CNN Network framework
[Figure 8: see original paper] Network structure of ResNet50

The ResNet50 architecture utilized bottleneck blocks with 1$\times 1, 3\times 3, and 1\times$1 convolution layers, incorporating stride operations for downsampling and batch normalization for stable training. The final fully connected layer was adapted for seedling classification with softmax activation.

Parameters of ResNet50

2.4 Training Configuration Model training was conducted on a high-performance computing workstation equipped with an Intel CPU E5-2683 v3, GTX 1070Ti GPU with 8GB memory, and 128GB system RAM. The software environment comprised Python 3.6, Anaconda3, and TensorFlow 1.13.2. Stochastic Gradient Descent (SGD) optimizer with momentum 0.9 was employed, with an initial learning rate of 1e-3 decaying over 20 epochs. The training batch size was set to 256, with 500 iterations per epoch.

[Figure 9: see original paper] Loss value curve of Faster R-CNN

3. Results

3.1 Model Performance Evaluation The optimized Faster R-CNN achieved superior performance compared to the VGG-based baseline. On the HTPP test set, the ResNet50-based model attained 95.67% precision on sunny days and 91.36% on cloudy days. UAV platform performance was slightly lower at 91.43% and 89.77% for sunny and cloudy conditions, respectively, reflecting the challenges of aerial imaging.

Comparison of output results of Faster R-CNN based on VGG and ResNet in the test set
Comparison of the output results of the model in the images of HTPP on sunny and cloudy days
Comparison of the output results of the model in the UAV images on sunny and cloudy days

Performance metrics included Precision, Recall, Mean Average Error (MAE), and Intersection over Union (IOU). The IOU threshold was set at 0.7 for positive detection, with Non-Maximum Suppression at 0.3. The model demonstrated robustness across different maize varieties and planting densities.

[Figure 10: see original paper] The effect of maize seedling detection on visible light images acquired by HTPP and UAV under different lighting conditions

3.2 Dynamic Monitoring Analysis Time-series data from HTPP enabled continuous monitoring of emergence dynamics. The model accurately tracked seedling counts over 10-12 day emergence periods, with results closely matching manual observations. The precision-recall curves indicated stable performance across temporal sequences.

[Figure 11: see original paper] P-R curves of two phenotypic platforms on cloudy and sunny days
[Figure 12: see original paper] The curves of the number of maize emergence

Statistics of the number of days required from emergence to end of different varieties and different densities

4. Discussion

The integration of ResNet50 with Faster R-CNN significantly improved detection accuracy for small-scale seedlings in complex field environments. The HTPP platform' s ground-level, high-resolution imagery provided better performance than UAV data, though both met practical application requirements. The model's generalization across lighting conditions and planting configurations demonstrates its potential for large-scale deployment in precision agriculture.

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Note: Figure translations are in progress. See original paper for figures.