Drone-Based Multi-spectral Pipeline for Detecting Abnormal Potato Strains in the Field

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ABSTRACT

Background: Potato is one of the most important crops for global food security due to its high yield and nutrition values. To decrease the impact of pest and disease damage to its yield, frequent manual visual inspection is often required for removing those infected and abnormal plants at an early stage. Such manual inspection is a burden for growers due to its heavy workload and reliance on the observers' experience. **Challenges**: Some researchers are developing drone sensing technology to address this problem. However, due to the resolution limitations of the drone-captured images, it is currently difficult to distinguish abnormal plants individually. Achieving high resolution would require close-range (low altitude) flights, but the drone rotor downwash effect causes the leaves to sway and blur. **Objectives**: Hence, we try to establish an pipeline for detecting abnormal potato plants using drones to achieve labor savings and production stability in seed potato farming. **Methods**: We developed a pipeline with the following steps: (1) develop batch processing scripts to obtain time-series orthomosaic, elevation, and multi-spectral maps for potato fields. (2) optimize the EasyIDP tool to find the corresponding positions in the original drone images from the generated time-series maps to decrease the effects of blurriness and resolution. (3) extract traits including plant coverage, plant height and NDVI, also conducting ground surveys to serve as training data for training machine learning detection model. **Results and Conclusion**: This pipeline has been partly tested in the experiment plots in *Nagasaki* and *Hokkaido*. Additionally, we plan to integrate this pipeline into open-source software to facilitate ease of use. The detected positions support being exported as standard formats for navigation apps, guiding farmers to remove them efficiently. **Funding**: This study was funded by Nagasaki Agriculture & Forestry Technical Development Center.

Keywords: Terrestrial LiDAR, volume estimation, 3D point cloud analysis, varying voxel

INTRODUCTION

Frequent manual visual inspections for detecting infected and abnormal plants are often necessary to decrase their impact on potato yields. To reduce inspection workload and minimize reliance on the observer's expertise, several studies have developed drone-based close-range sensing techniques to address this issue. (Kouadio et al., 2023). Although the feasibility of combining multi-model sensors and machine learning detection algorithms has been tested in experimental fields, challenges such as "data acquisition and processing efficiency" and "diverse testing scenarios" still leave room for improvement (Kouadio et al., 2023). Meanwhile, the quality of plants on photogrammetrically produced maps is often compromised by blur and sway due to rotor downwash effects. While raw images can achieve leaf-level detection resolution (Van De Vijver et al., 2022), the processing steps required to convert pixel detection results into geographical positions are complicated without convenient tools available.

Thus, this study tried to implement publicly available pipelines or tools aimed at (1) improving data processing efficiency and (2) testing feasibility in more diverse scenarios in Nagasaki and Hokkaido.

MATERIALS AND METHODS

The workflow of proposed pipeline is illstrated in **Figure 1**. First, we developed several Python scripts based on the Metashape API (Agisoft LLC, St. Petersburg, Russia, commercial photogrammetry software) for nearly automatic batch processing of collected drone images (**Fig. 1.1**). These scripts automatically export the generated time-series orthomosaic, digital elevation, and multi-spectral maps (**Fig. 1.2**). Next, based on row and sowing distances, a grid was generated to cover individual plants (**Fig. 1.3**). For each individual grid, traits such as fraction vegetation cover (FVC), mean height (mHT), and mean NDVI (mNDVI) were calculated. Specifically, our previously implemented EasyIDP tool (Wang et al., 2021) was modified to find corresponding positions on raw images to obtain more accurate FVC estimates (**Fig. 1.4**). Ground truth was obtained through ground investigation for creating training and validation data in *Nagasaki* (**Fig. 1.5**). This dataset was then used to train and compare several existing machine learning or deep learning classification models (**Fig. 1.6**). Later, the generated model will be applied to the next year's data and in *Hokkaido*. Finally, the abnormal detection results will be exported to an XML file compatible with the Google Earth mobile app, enabling field removal operations.

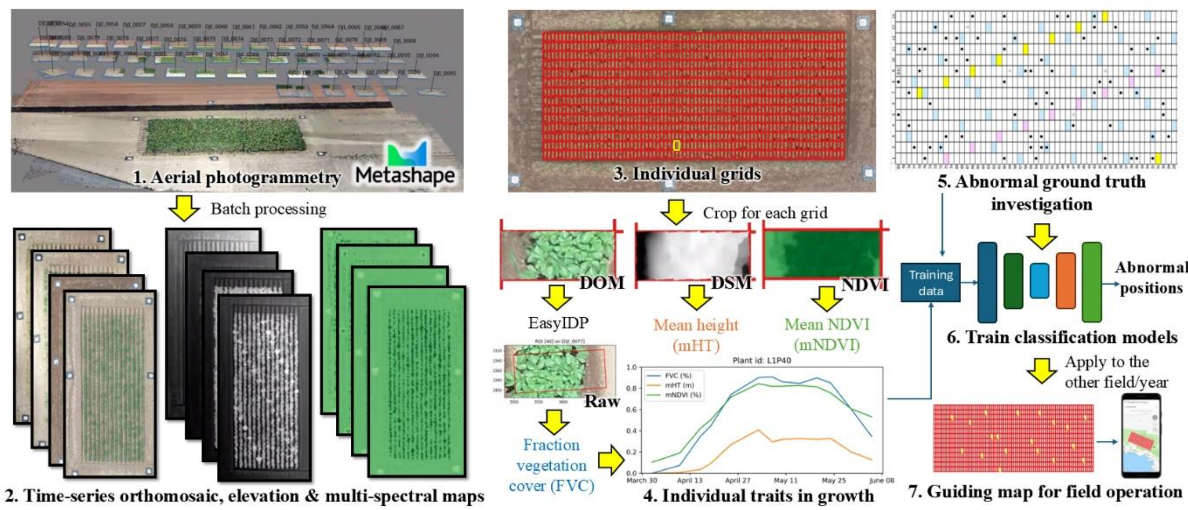

Figure 1. Workflow of proposed pipeline for detecting abnormal potato strains

RESULTS AND CONCLUSIONS

In this study, we contributed to developing a pipeline for detecting abnormal potato strains, with the goal of increasing data processing efficiency and testing in diverse scenarios. All documents, scripts, and code for this pipeline will be made available at https://github.com/UTokyo-FieldPhenomics-Lab/UAV-Abnormal-Potato. The pipeline includes: (1) scripts for batch generating time-series aerial photogrammetry products, (2) instructions for creating individual grids using QGIS, (3) scripts for estimating individual traits, (4) scripts for training and applying machine learning models, and (5) scripts for exporting results to the Google Earth App. In the near future, after the feasibility of these scripts is tested, a web-based GUI will be developed for more widespread and user-friendly use.

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