Crop Field Grassway Segmentation Using NAIP Satellite Imagery

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INTRODUCTION

The goal of this research project is to utilize images from the USDA’s Cropland Data Layer (CDL) [1] and National Agricultural Imagery Program (NAIP) [2] to extract submeter level features of crop fields.

We present a system to effectively and efficiently identify the grassway inside the crop fields. Grassway can create noise and negatively affect field-level crop monitoring since grass and crops have similar signals in moderate-resolution satellite images. Without an accurate grassway data layer, planted acreage can be heavily overpredicted and result in incorrect predictions of global food production. Accurate estimates of crop amounts is important for downstream analysis research tasks, including crop yields [3,4].

BACKGROUND

Our system utilizes satellite imagery taken at various resolutions. The Cropland Data Layer (CDL) is taken at 30-meter resolution and can be used to detect non-crop features at sub-meter level features of crop fields. CDL data is available each year but is only made available to researchers a few months into the next year.

The National Agricultural Imagery Program (NAIP) is taken at least 1 meter resolution (many images are at 60 cm) and can be used to detect high-resolution non-crop features such as grassways. Due to the high resolution, NAIP images are not taken and made available as frequently.

In this pipeline, the CDL and NAIP spectral bands (RGB, near-infrared) are used in conjunction.

METHOD AND RESULTS

Unsupervised Clustering

We first use k-means [5] to partition the image data into several clusters, then merge the clusters into crop, non-crop, and background pixels. K-means clustering finds k clusters and assigns pixels to clusters based on their distance to the mean. When performed on fields known to have more than 50% crops, this unsupervised approach is effective in determining which pixels correspond to crops and which do not.

When handling NAIP data, we extract the red, green, and blue channels and ignore the near-infrared due to the low classification accuracy.

We empirically determined that using k=5 (5 cluster centers) had the best results. A smaller k didn’t allow for differences in different types of crops, while a larger k took longer to converge with minimal improvement in the quality of the results.

When clustering on fields known to contain more than 50% crops (using information from CDL), we assume that the cluster with the most pixels is the crops and thus merge all the other clusters together into one using k-means again but with k=3 (3 cluster centers, one for crops, one for non-crops, and one for the background).

For CDL data, we must first reproject the CDL to the resolution of the NAIP image for the purpose of processing. We also mask the image so that both soybean corn and map to a single “crop” label for the purpose of segmentation.

CONCLUSIONS

Using NAIP and CDL images, the system is able to efficiently and effectively identify the grassways from crop pixels of a field. In future research, the proposed deep learning model will be implemented and fully evaluated. We will also explore other high-resolution satellite missions (e.g. 3-meter resolution), as these will have less noise to confuse models compared to sub-meter resolution images.

REFERENCES


