Visual Identification of Agricultural Features

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1. Introduction

Our project aims for identifying the centerline of crop rows as well as the weeds present between the rows in sample farmland images with multiple feature detection methods. The identification approaches, therefore, could help agricultural research such as determining planting distance and weed eradication.

2. Approach

2.1 Preprocessing

In the first step every pixel in the RGB image was compared to see if it had a larger red or green value. When the pixel had a higher green value, the green value would be kept otherwise the pixel was designated black. This was to eliminate any corner points that are not associated the plants. The resulting image was then cropped and can be seen on the right.

Then 7 percent of the image rows were selected at random. In each sampled row the number of transitions from grey to black was calculated which was supposed to give a good representation of the number of crop rows. The median number of transitions was used to minimize the influence of outliers. This gave an answer between 6 and 9 a majority of the time which was deemed an acceptable representation of the number of crop rows. This value would then used to set the number of clusters for the k-means algorithm.
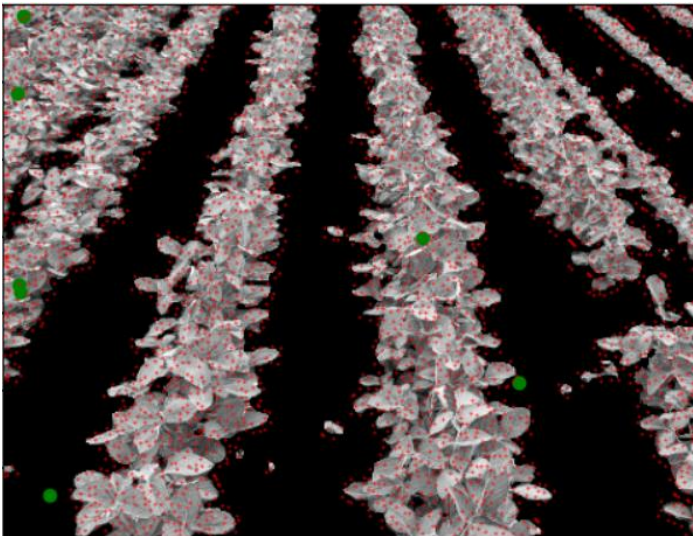
2.2 Crop Center Identification

### 2.2.1 Harris Corner Detection
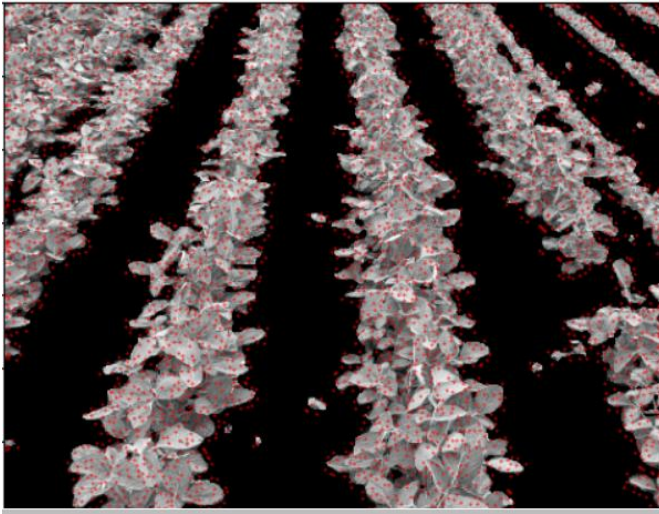
The Harris corner detector was run over the image to detect corners. The theory being the algorithm will detect the corner of leaves with the highest density of leaves occurring in the crop row. This turned out to be successful as seen in the image above.

2.2.2 K-Means & RANSAC

The corner points were then used as data points for k-means clustering algorithm. The resulting center of each cluster can be seen in green. The resulting clusters cross over several crop rows. This would produce a undesirable line for RANSAC which is why DBSCAN was investigated.

2.2.3 DBSCAN& RANSAC
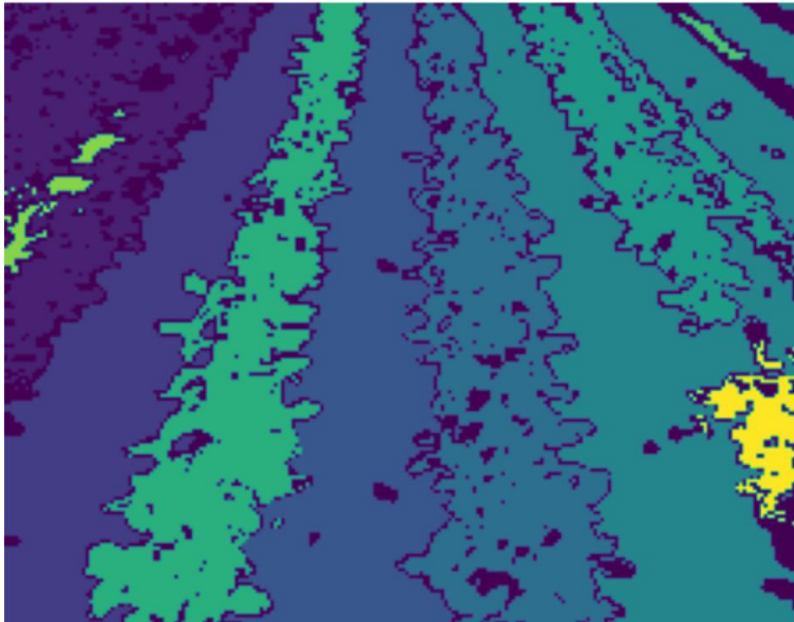
DBSCAN stands for Density-Based Spatial Clustering of Applications with Noise. The algorithm starts by selecting an arbitrary point in the dataset and considers a new point as a core point first, then loop around pixels near this point to verify if these points form a cluster based on the specified epsilon and minPts parameters. If the point is a core point, all directly reachable points will be appended to one cluster. Otherwise, the new point will be discarded as a noise. The process continues until all points have been visited.

In the result, we successfully divide the crops into 6 clusters, and each row of crops corresponds to a DBSCAN cluster.
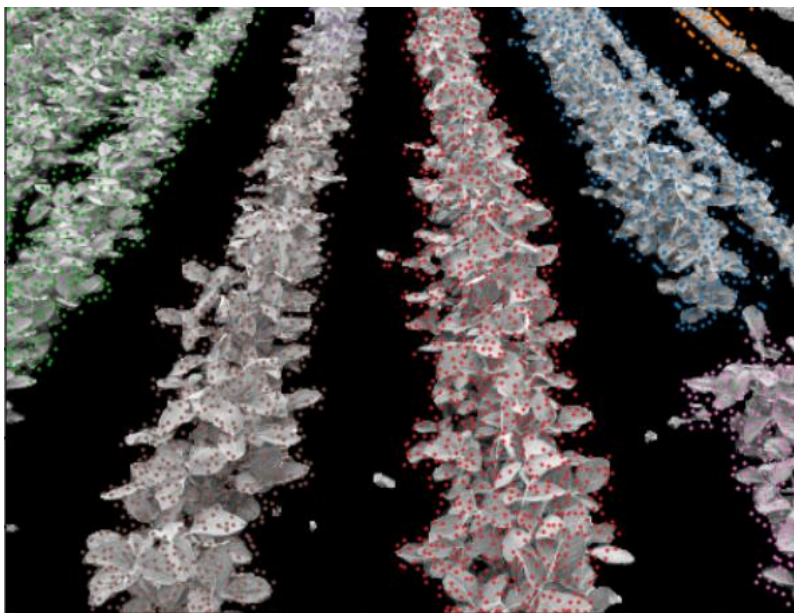
When density based DBSCAN is properly tuned, it gave the results above where each color belongs to a cluster. This result was much more desirable with each crop row roughly belonging to one cluster.
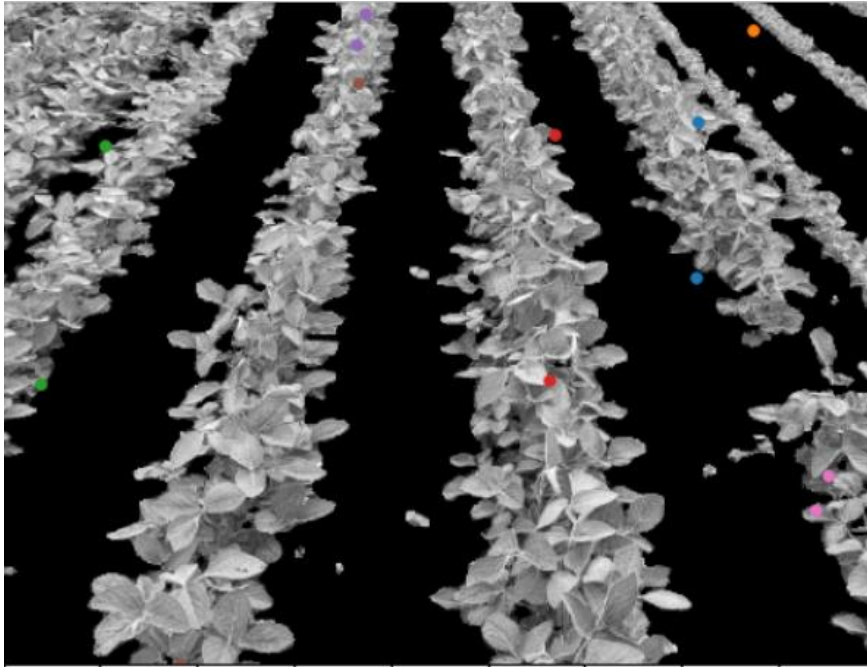

In this variation of RANSAC two random points were selected from each cluster and a line was drawn through them. Two parallel lines were then drawn 60 pixels away from the existing line. The number of cluster points between the two parallel lines was counted and recorded as inliers. The algorithm then selected two different random points in the cluster and repeated the process and the result with more inliers was kept. This loop was completed 1,000 times per cluster. The random points witch produced the best results per cluster can be seen above. As you can see this had mixed results with the two brown points being centered in its respective row while the blue and red have at least one point off the center. This could potentially be improved by tuning parameters such as the number of iterations and the number of pixels the parallel lines are apart.

2.3 Weed Identification

In our input image Mod_Pressure, there are parallel rows of broadleaves crops, among which exit grass weeds. Given a template of broadleaf or grass model from the original farmland image, we locate the exact position in the larger land. The kind of application could help agricultural research on the relationship between planting space and the appearance of weeds.
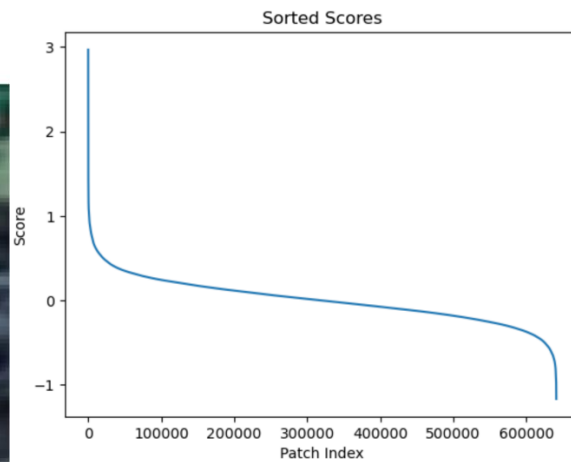
Broadleaves vs Grass
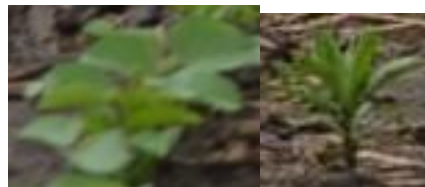
2.3.1 Template Matching with NCC


Patch 1 (NCC Score: 2.742923828002942)

Sorted NCC Scores
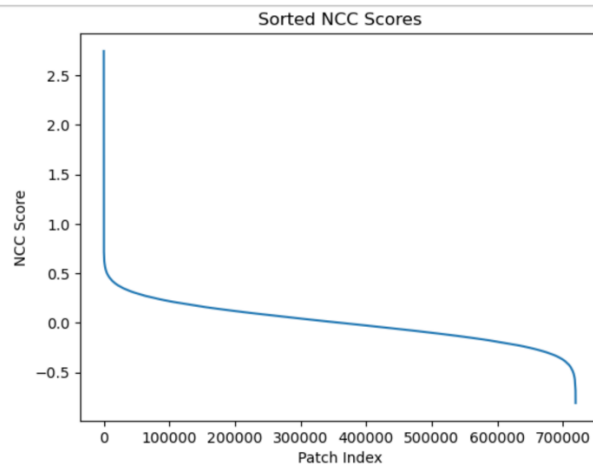
Patch 1 (Score: 2.968926706616002)

Sorted Scores

NCC (Normalized Cross-Correlation) matches patches to the template accurately. Both grass and broadleaves samples are correctly recognized.

2.3.2 Template Matching with SSD

Patch 1 (Score: 183.65625929229853)

Sorted Scores

Patch 1 (Score: 49.30760439560439)

Sorted Scores
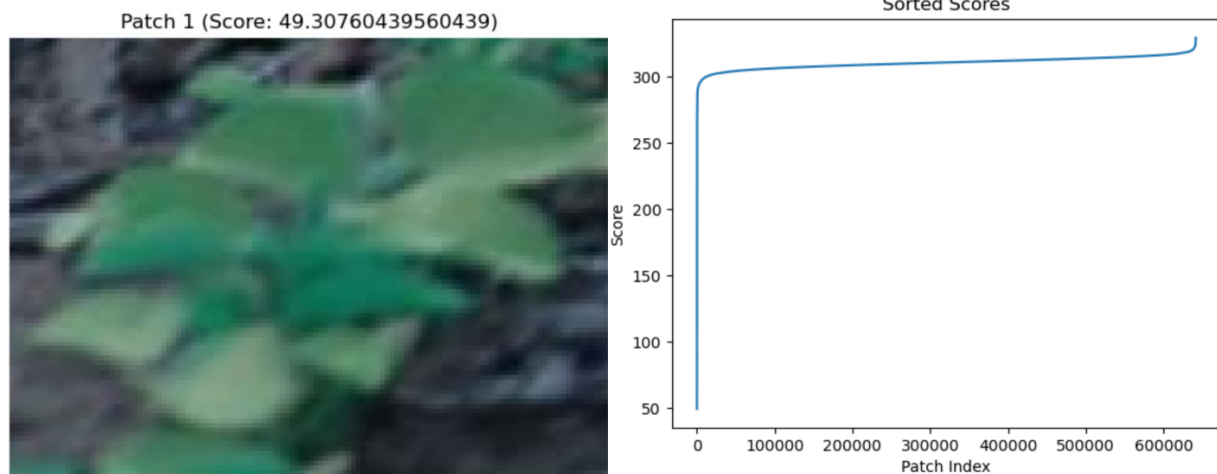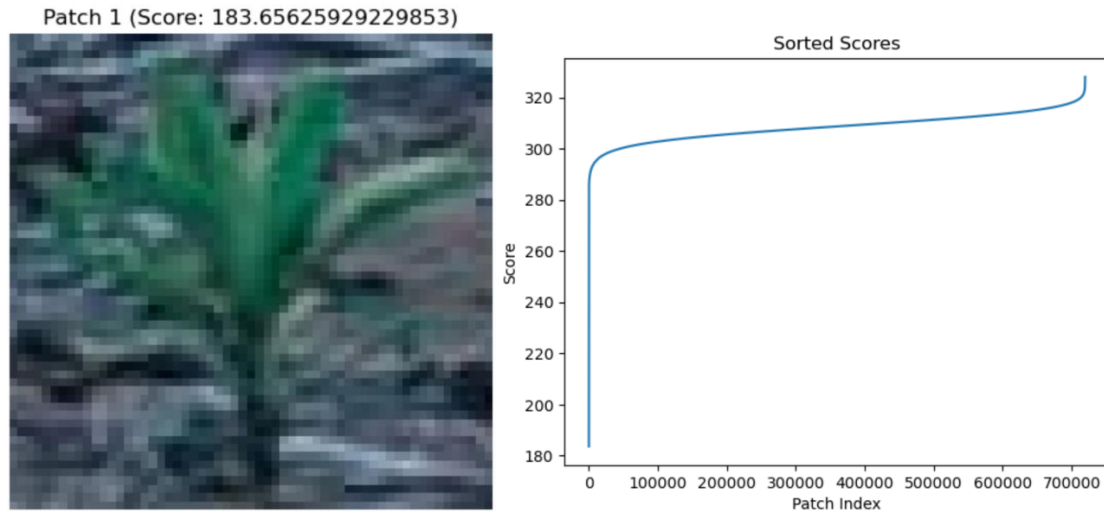
SSD (sum-of-squared difference) also correctly identifies the template in the original image. The order of scores should be different with NCC, because lower difference means higher similarity between patches and the template.

2.3.3 Template Matching with SAD

Patch 1 (Score: 218.0225988700565)

Sorted Scores

Patch 1 (Score: 299.44167032967033)

Sorted Scores
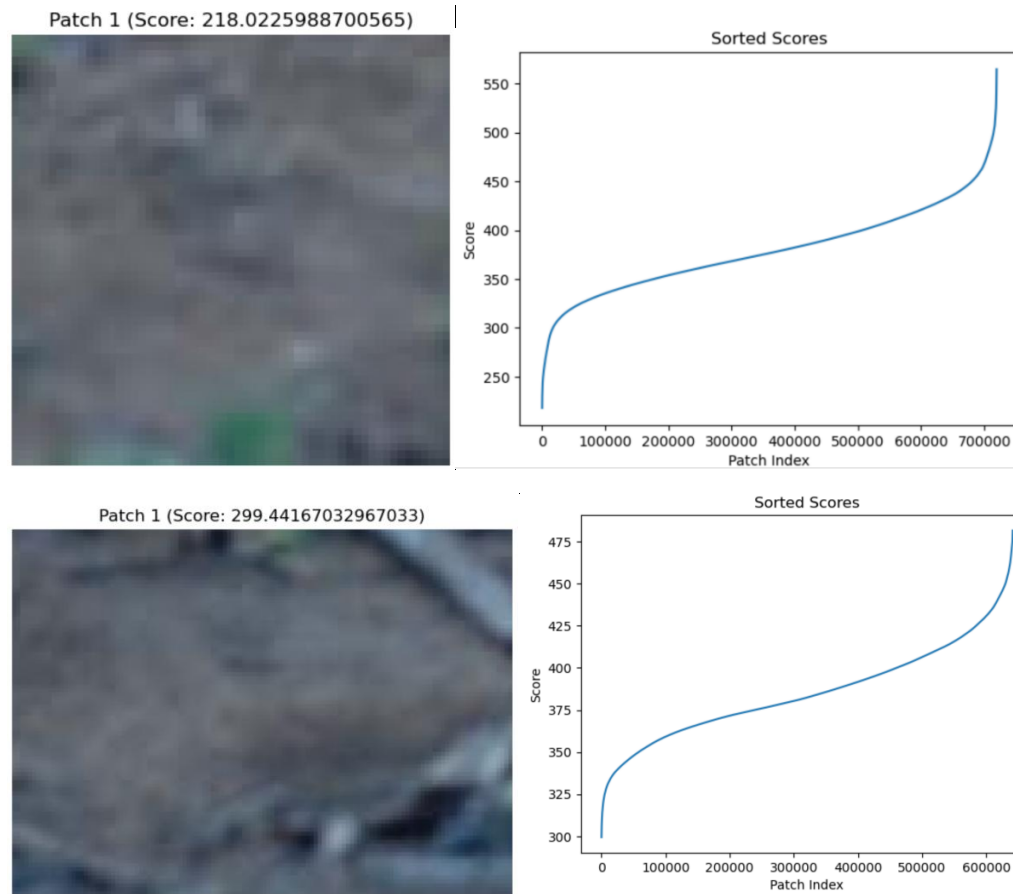
SAD (sum-of-absolute difference) failed to identify the template for either method as the result suggests. This might attribute to the noise in the image. So compared to SAD, NCC and SSD are more reliable to find similar patches to the template.

3. Work Breakdown

Bobby Bench: Preprocessing, Harris Corner Detection, K-Means, RANSAC

Yihang Yang: DBSCAN, Template Matching