Cornell University

Computer Vision ECE5470: Project Presentation

Distance Measurement in Sugar Cane Rows to Determine Replantation using Aerial Imagery.

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Group #3
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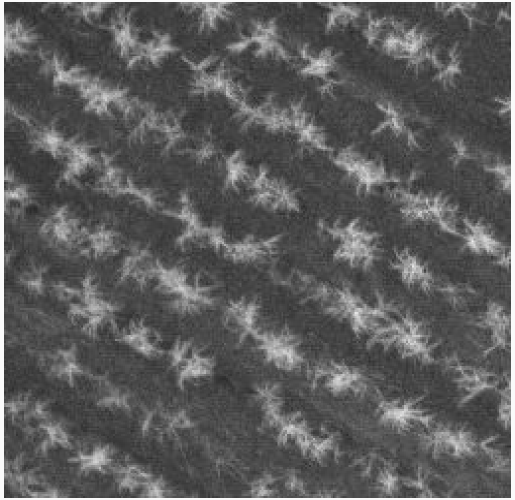
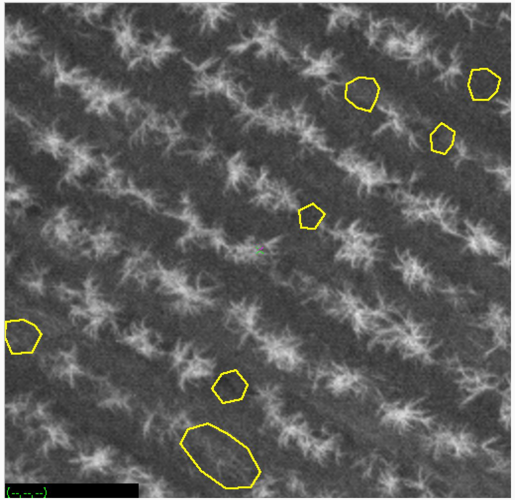
The Problem

Identify and highlight gaps between sugarcane crops in each row to designate regions for replantation due to the reduction of productivity in each growing cycle.



Input: Near Infrared (NIR) Aerial Image



Output: Image with gaps annotations

Significance

Sugarcane is an important economic resources for many tropical countries. *(Luna and Lobo 2016)*

- Studies say gaps between crop regions correlate with planting quality
- Best way to maximize yield is to <u>minimize occurrence of gaps between crop regions</u>
- Currently, trucks pull sensors around crop field
  - Labor intensive and time intensive
  - Not sufficient intensity for detailed spatial mapping
  - Mapping gap density critical to crop evaluation
- Imaging crops aerially will save time and help with crop yield efficiency

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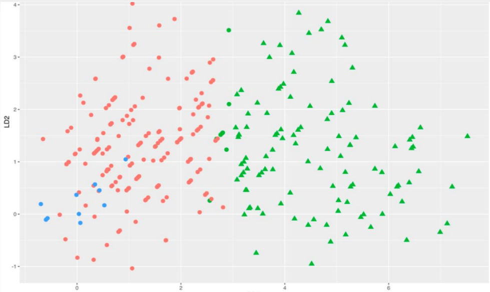
Gap Percentage	Planting Quality	Observations
0–10	Excellent	Exceptional germination conditions
10–20	Normal	Most common type observed
20–35	Subnormal	Possibility of renewal may be considered
35–50	Bad	Renewal should be considered
>50	Very bad	Renewal/Replanting

Table 1 (*Luna and Lobo 2016)*

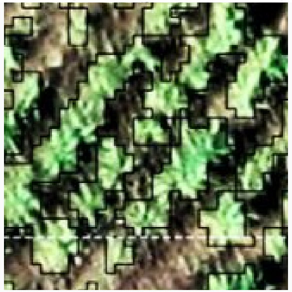
Previous Work:

Support Vector Machine using Class Identifiers for each Region *(Luna and Lobo 2016)*

Plant Identification in Mosaicked Crop Row Images for automatic emerged corn plant spacing measurement *(Tang and Tian 2008)*



1



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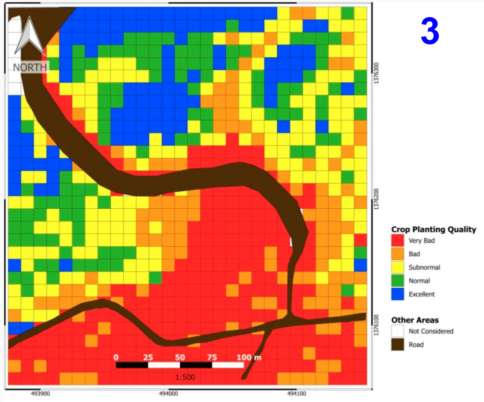

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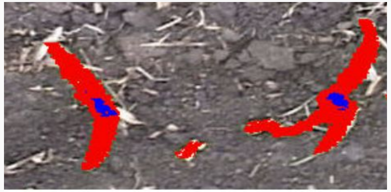
1. Class Identifiers 2. Class Identifier boundaries
3. Output: Crop Planting Quality Evaluation

(All Images Obtained from Luna and Lobo's 2016 Article)

1



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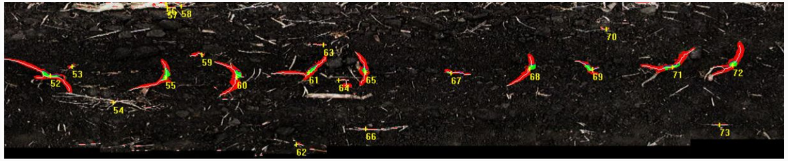

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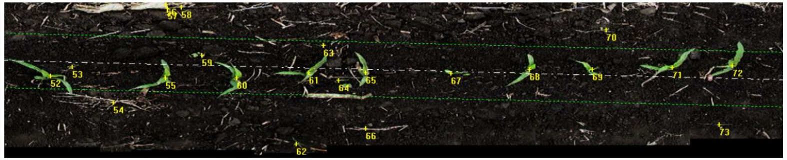

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1. Input 2. Identify Corn stalk and leaves
3. Count individual crops 4. Apply centerline fitting

(All Images Above Obtained from Tang and Tian's 2008 Article)

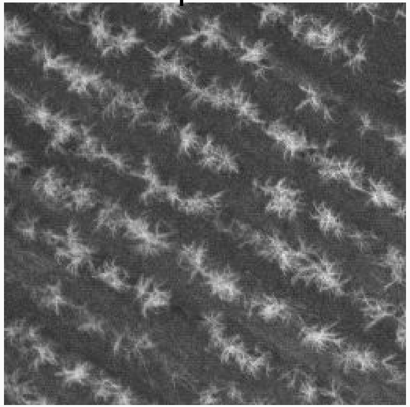
The Issues

- Issues we have faced:
  - Determining row orientations
  - Measuring distance between crop regions within each row
  - Losing information when thresholding crops
  - Image luminosity not completely consistent throughout data sets
- Issues specific in each part:
  - Hough transform generates a lot of phantom lines
  - Filtering in hough domain, variable thresholding values
  - Hough transform trouble finding lines in the edge of the crop and not in the COM
  - In rows with a few crops, hough transform is not able to find a line approximation.
  - Getting a good background subtraction
  - Irregular crop shapes
  - Difficult to approximate to a regular shape to find the distance between crops.

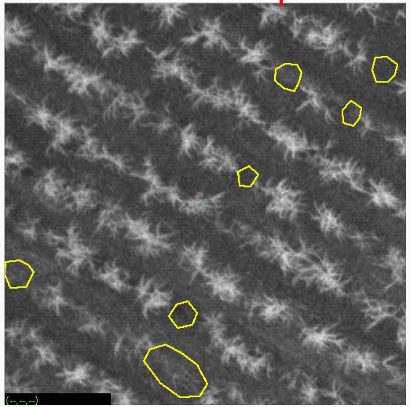
The Algorithm: Overview

- We thought we could simplify from class identifiers
  - Used concept of crop density and combined with other work
    - Use hough line transforms to identify rows within a sugarcane field
      - After identifying rows, measure distance between crops within the row
- Identifies regions in each row where sugarcane should be replanted to maximize yield from sugarcane field

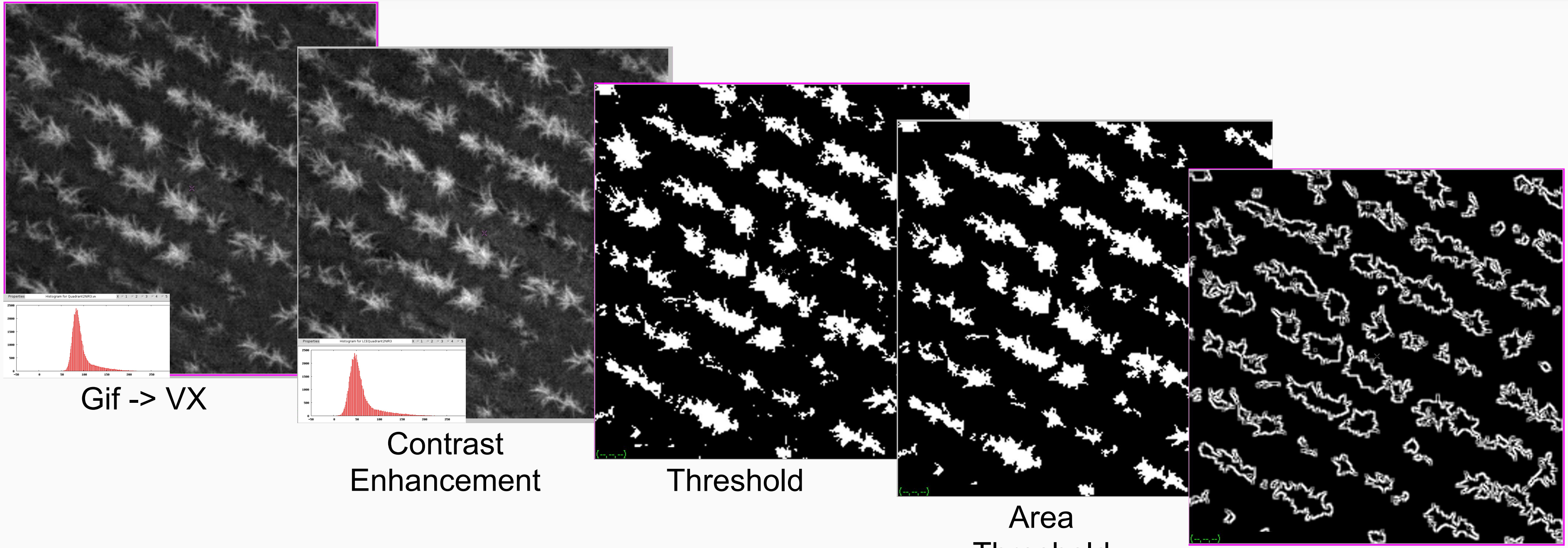
Input



Theoretical Output



The Algorithm



Gif -> VX

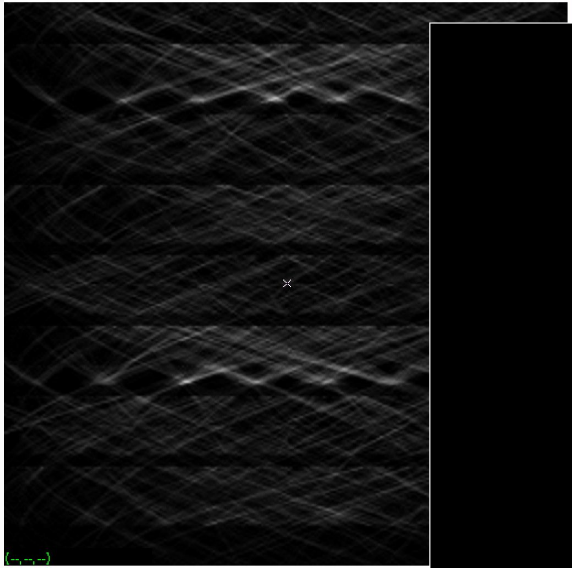
Contrast Enhancement

Threshold

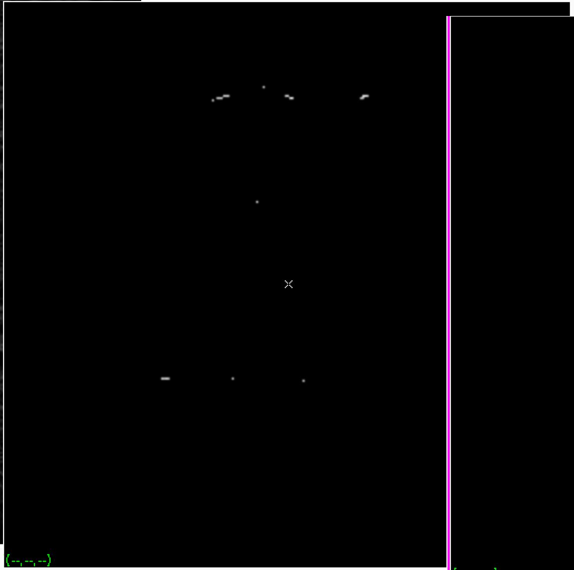
Area Threshold

Edge operator

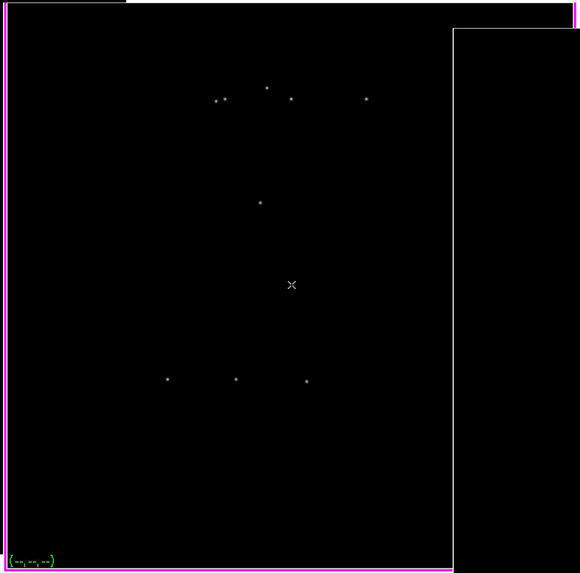
The Algorithm: Process



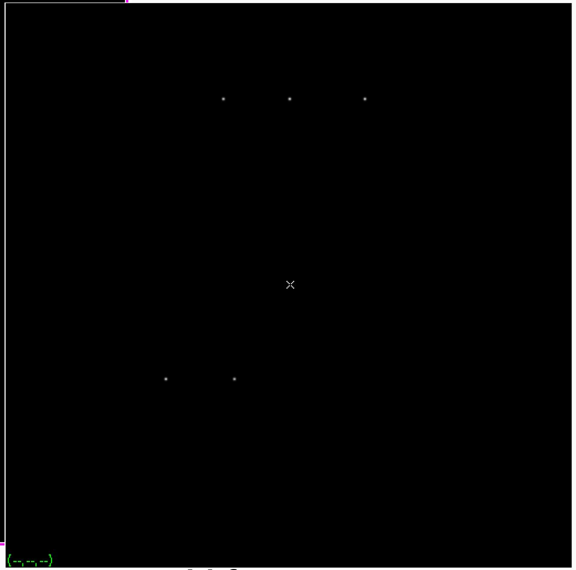
Hough line transform



High Range Threshold

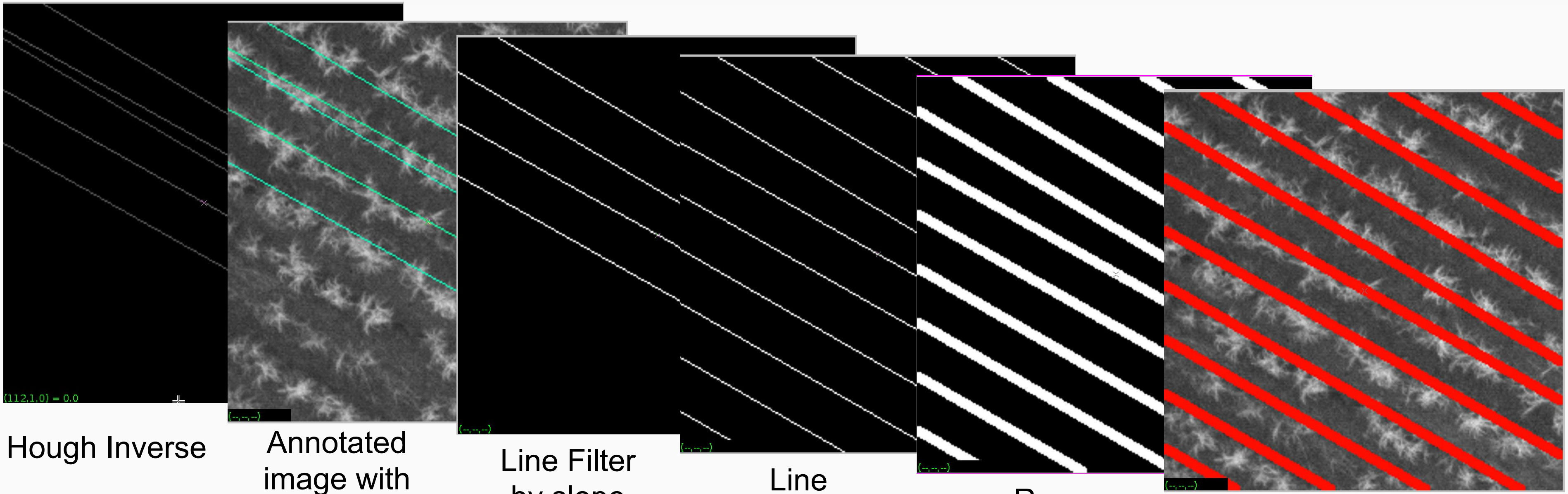


COM



Y-frequency filter

The Algorithm: Process



Hough Inverse

Annotated image with Hough Inverse

Line Filter by slope

Line reconstruction

Row Reconstruction

Annotated image with Rows

The Hypothesis

Our project should be able to determine all regions for replantations within an aerial infrared image of a sugarcane field:

- First, segment crop regions
- Next, identify rows
- Finally, perform distance calculation between crops in respective rows and highlight regions

Right now we use the dice similarity coefficient to compare the crop segmentation and the row identification

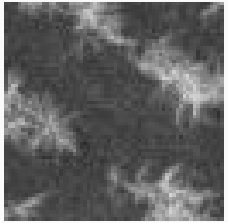
Using concepts from both sugarcane gap density SVM algorithm and corn plant identification algorithm::

- gap distance for evaluation metric of planting quality
- statistics and hough transforms instead of line fitting in order to find rows and identify crops within same row

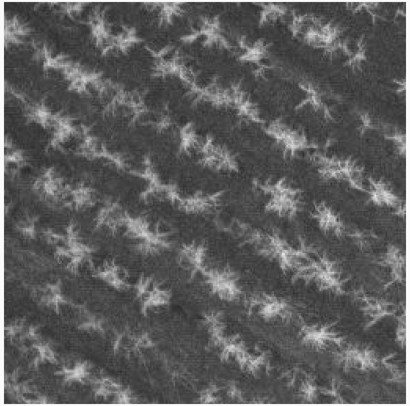
The Experiment - data

Data Set: Multispectral Images taken by fixed wing drone in the coast of Ecuador of a sugarcane plantation.

- Number of images: 10
- Camera: MicaSense Red Edge
- Format: 8 bit TIFF
- Resolution: 512 x 512 pixels
    - Crop segmentation: 64 x 64 pixels (cropped)
    - Row identification: 256 x 256 pixels (cropped)
- Spectral band: Near Infrared - NIR (825-860 nm)
- Field of View: 47.2 HFOV
- Ground Sample Distance: 8 cm by pixel at 120m
- Altitude: 100 m aprox.



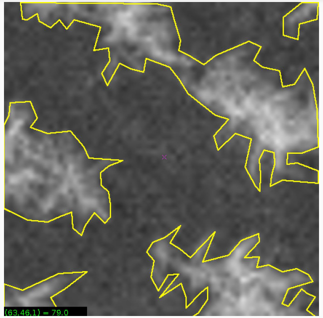
Sample Image
Crop segmentation

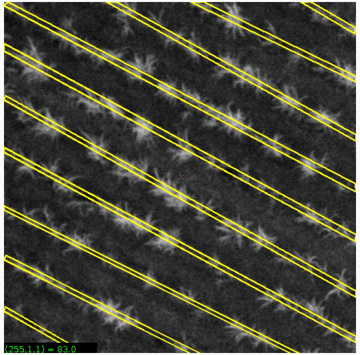


Sample Image
Row segmentation

The Experiment - method

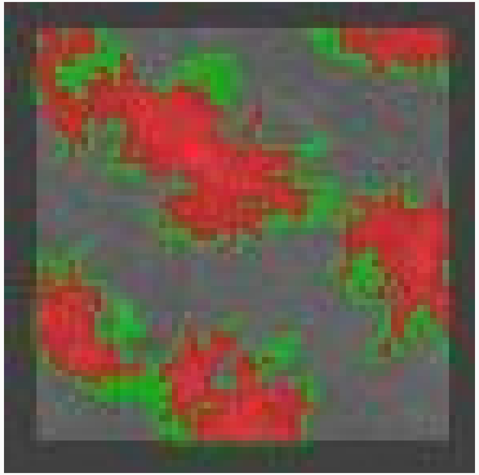
- Experiment Details:
  - Crop Segmentation:
    - Divided arbitrary data set images into 64 x 64
      - Easier to annotate crop regions in smaller image
    - Applied our algorithm's threshold part to modified input image to get segmented crop image
    - Compared output with annotation using visionX command
  - Row Identification
    - Divided arbitrary data set images into 256 x 256
      - Annotated ~6 pixel line bisecting center of each crop row
    - Applied our algorithm's row identification and reconstruction to get an image with lines that should be inside the crop rows
    - Manually compare the output with annotation





Results:

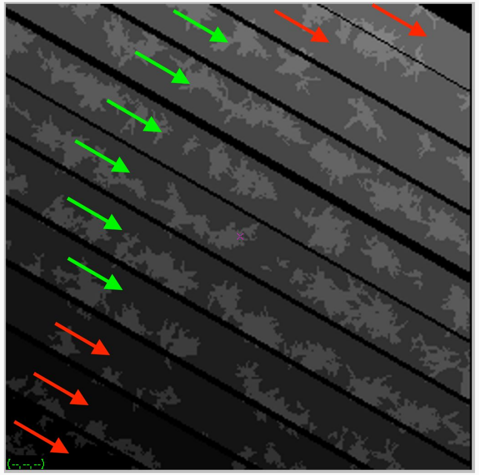
Crop segmentation



similality_avg= 0.52
sensitivity_avg= 0.94
specificity_avg= 0.73
DiceCoeff_avg= 0.40

sim	0.64732
sens	0.99471
spec	0.54642
dsc	0.48967

Row Identification



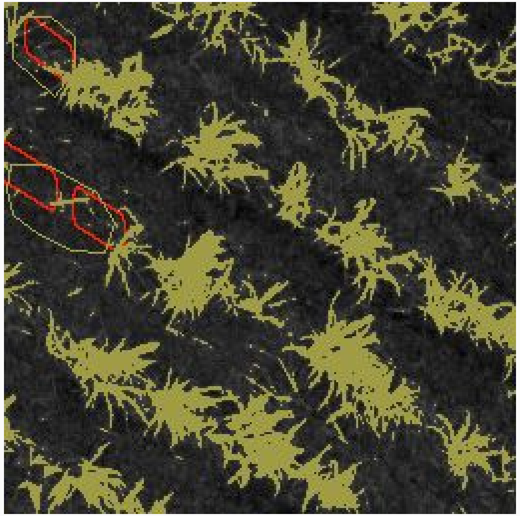
[DC]_average=0.702
[PR]_average=0.63

Dice coefficient [DC]=2*tp/(2*tp+fn+fp) =2*6/(2*6+0+5)=12/17=***0.705***

Probability of recognition [PR]=#Correct Recognized Rows (algorithm) / #Total Rows (ground truth) = 6/11=***0.54***

Results:

Final Output



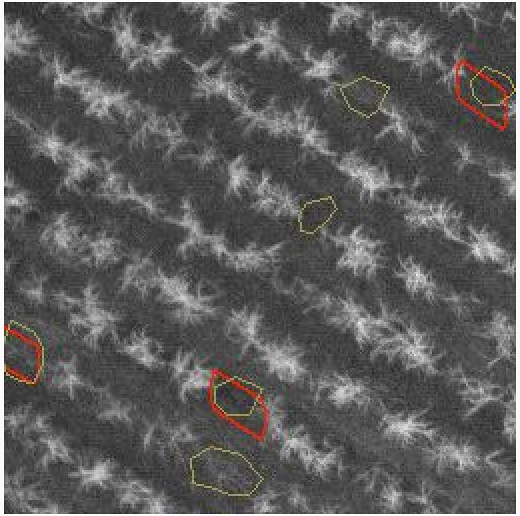


Image	Dice coefficient	Probability of Recognition
1	1	1
2	0.57	1
3	0	0
4	0.8	0.8
5	0.66	0.5
6	0.75	0.75
7	0	0
8	0.88	0.5
9	0	0
10	0.6	0.6
Average	**0.54**	**0.52**

Discussion & Summary

- Crop segmentation
  - For the most part identified crop regions without any false positives
  - Could have applied better preprocessing and normalization to each image in data set
  - Did not approximate crop area the best
- Row Identification
  - Much more trouble than we anticipated
    - Filtering out phantom lines hard
  - Could not get row identification to work well on all images
- Main Takeaway:
  - Applying statistical filters will improve results usually
    - We understand now why people we’re using SVMs to solve this problem
  - Dynamic Hough space filtering is tough
    - Difficult to calibrate it for all the different images in data set
    - The bigger an image is (more crops), the better the results because there will be more hits at the points we want in the hough domain