Detection of Sugarcane Crop Rows From UAV Images Using Semantic Segmentation and Radon Transform

Renato Rodrigues da Silva

Advisors: Prof. Dr. André Ricardo Backes and Prof. Dr. Mauricio Cunha Escarpinati

Universidade Federal de Uberlândia
Programa de Pós-Graduação em Ciência da Computação

Summary

1. Introduction
2. Fundamentals
3. Methodology
4. Experimental Results
5. Conclusions

1. Introduction

Agriculture Scenario

- Sugarcane is one of the most planted cultures in the planet;
- Brazil is the largest producer of sugarcane and ethanol in the world;
- Around 10,123.5 Mha planted in the 2018/2019 harvest;
- Impacts.

Precision Agriculture (PA)

Figure: Example of precision agriculture equipment developed for farm management and tasks such as high precision positioning systems, laser land levelling, and precision seeding/fertilizer/irrigation/harvesting, extracted from (LI et al., 2020).

Unmanned Aerial Vehicles (UAVs)

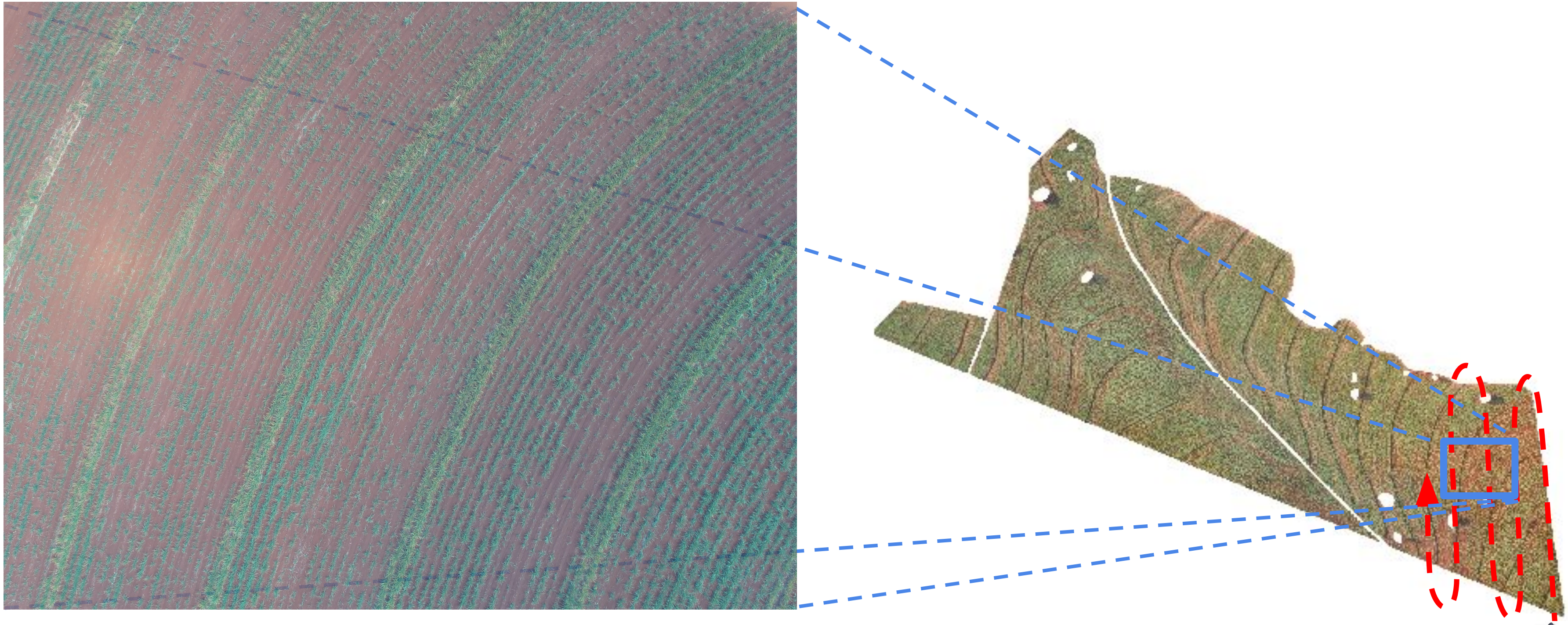


Figure: Example of sugarcane crop image taken by a UAV composing an orthomosaic.

Motivation

- Changes in the crop scenario:
  - Seeding failures;
  - Death;
  - Erosion;
  - Plant tipping;
  - Animal interventions.

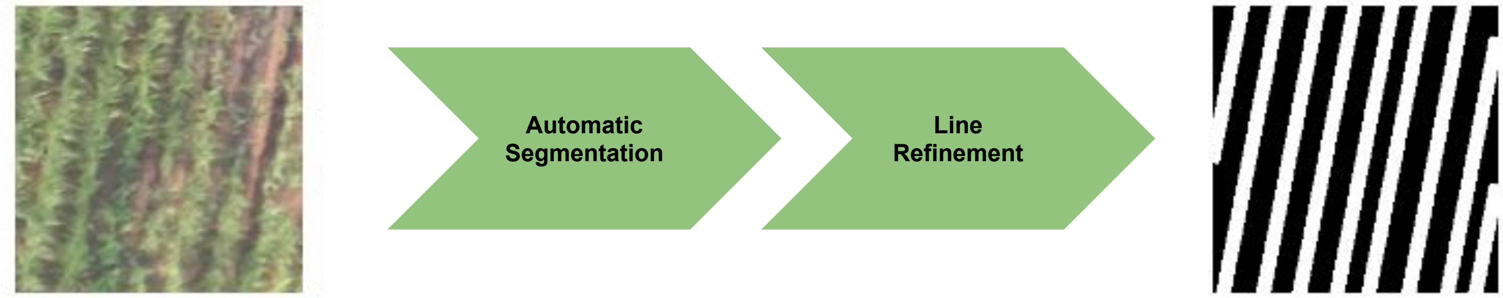
Motivation

Figure: Example of crop-row identification performed manually by an expert (left). Example of an autonomous machinery it is being guided by the detected crop rows. CommandCenter™ Premium produced bu John Deer, extracted from https://www.agriexpo.online/prod/john-deere/product-169419-2710.html

Motivation - state of the art

- Hough transform:
  - BELTRAMETTI; ROBBIANO, 2012;
- Otsu Method:
  - MONTALVO et al., 2013; etc.;
- Convolutional Neural Networks:
  - PANG et al., 2020; etc.

Proposed Approach



2. Fundamentals

Convolutional Neural Network (CNN)

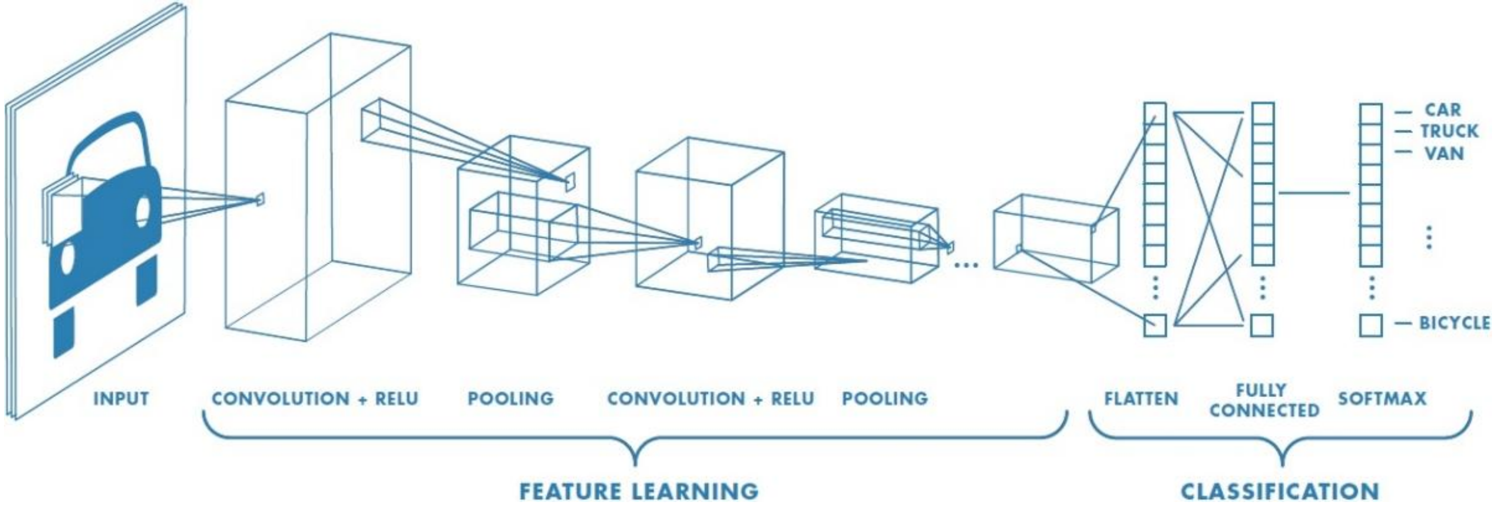


Figure: Example of a network with convolutional layers, extracted from https://www.mathworks.com/solutions/deep-learning/convolutional-neural-network.html

CNN - Convolution Filter

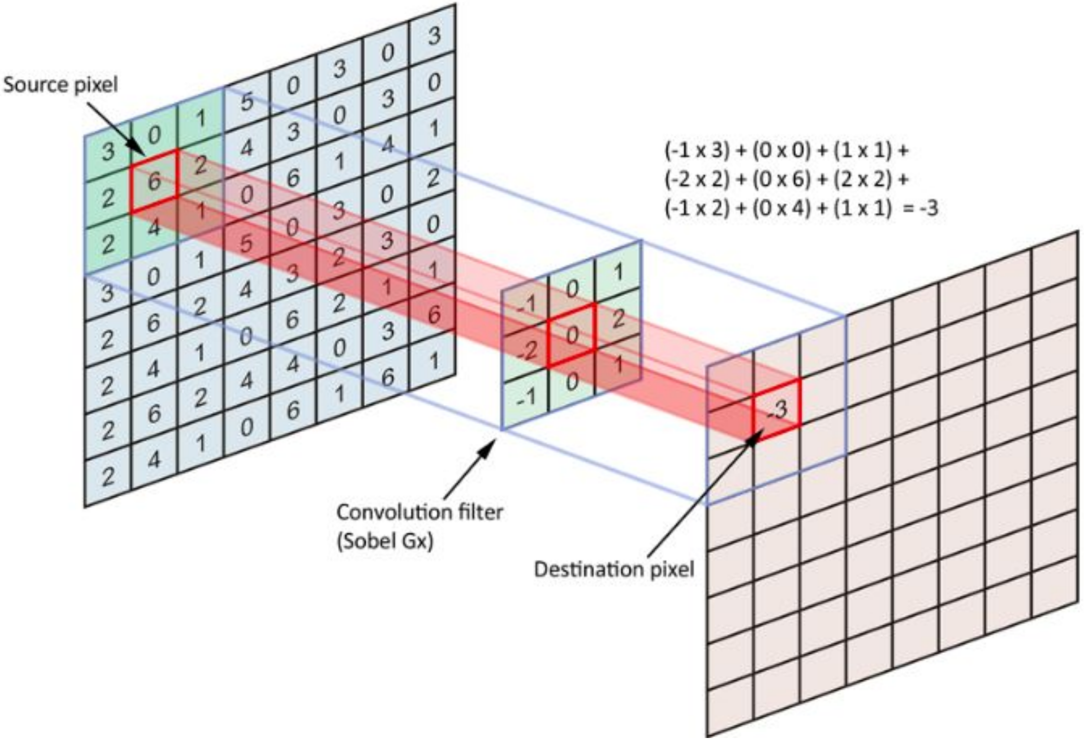


Figure: A convolution filter, extracted from
https://cdn-images-1.medium.com/max/1600/1*EuSjHyyDRPAQUdKCKLTgIQ.png

Image Segmentation

- Subdivide an image into specific regions;
- One of the most difficult steps in Digital Image Processing (DIP);
- Directly impacts the result of other processing steps;

Semantic Segmentation

- Semantic Segmentation Networks (SSNs);
- Various levels of abstraction;
- Examples of SSNs/CNNs: U-net, PSPNet, LinkNet, etc.

Semantic Segmentation

Segments	%
Vegetation	43.39
Road	30.91
Building	9.62
Fence	6.63
Sky	4.17
...	...

Segments	%
Vegetation	45.32
Road	32.55
Building	9.92
Sidewalk	4.69
Sky	3.40
...	...

Segments	%
Vegetation	56.47
Road	25.93
Building	6.13
Sky	5.42
Fence	2.64
...	...

Figure: Example of a semantic segmentation performed in some images, their results,as well their classifications and respective percentage score per segment/label.Extracted from (NAGATA et al., 2020)

Genetic Algorithm

- Rely on bio-inspired operators such as mutation, crossover and selection;
- Starts with an initial population of individuals, where each-one is assumed to be a solution to the problem to be solved.

Radon Transform

- Spectral reconstruction of an object;
- A projection of a 2-D image *f(x, y)* is a set of line integrals;
- Reconstruction based on projections of lines;

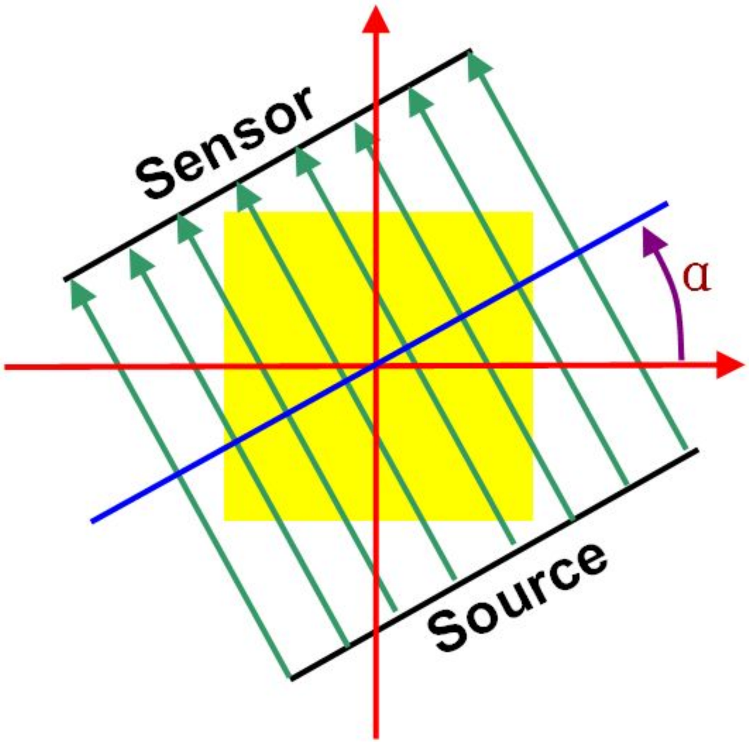


Figure: Example of Radon transform being applied to a object reconstruction, extracted from https://www.globalsino.com/EM/

4. Methodology

Datasets

- Four test mosaic images of different sizes;
- SenseFly S.O.D.A. camera 5472 × 3648 pixel resolution (RGB lens F/2.8-11, 10.6 mm);
- GSD: 0.053 meters (5 cm of ground per pixel).

Figure: fixed-wing UAV SX2 made by Sensix Innovations and responsible for capturing the imagery used in this work.

Datasets

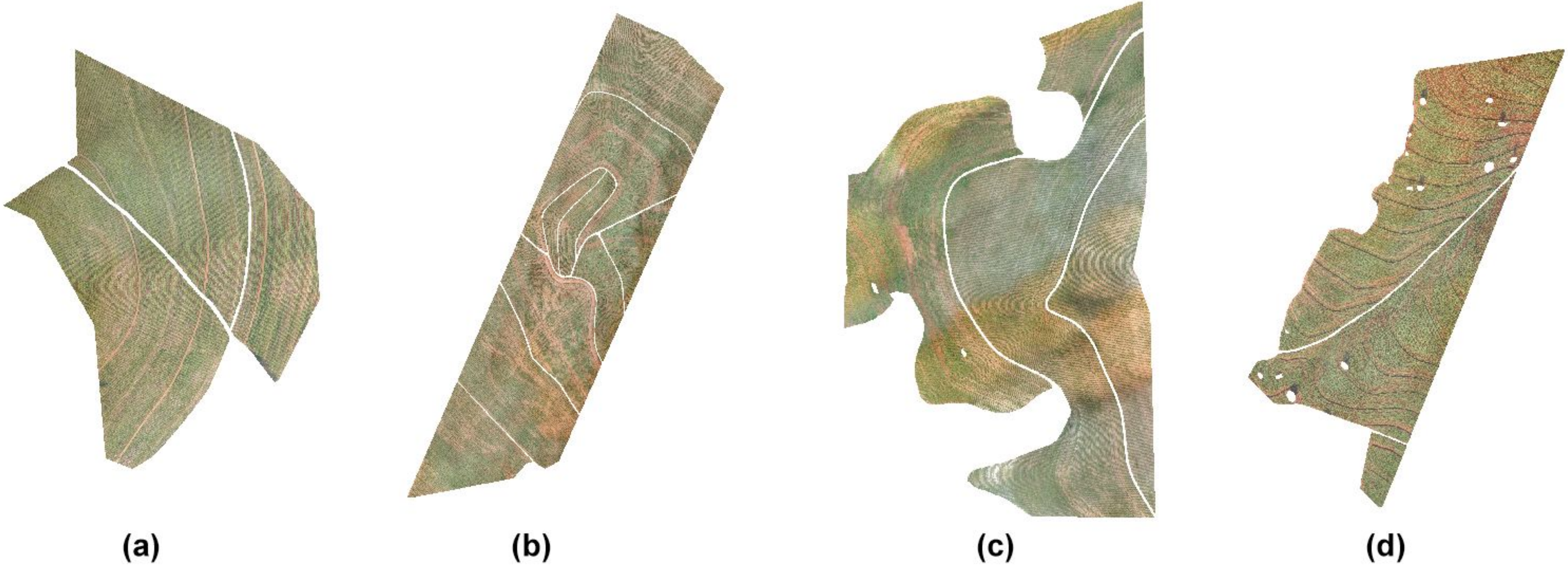


Figure: Test images used to evaluate our approach and their respective sizes: (a) 11180×8449; (b) 19833×30255; (c) 17497×10771; (d) 16677×24181.

Plant Cane and Ratoon Cane

(a) (b)

Figure: (a) example of cane in the ratoon phase. (b) example of plant cane.

Segmentation Reference

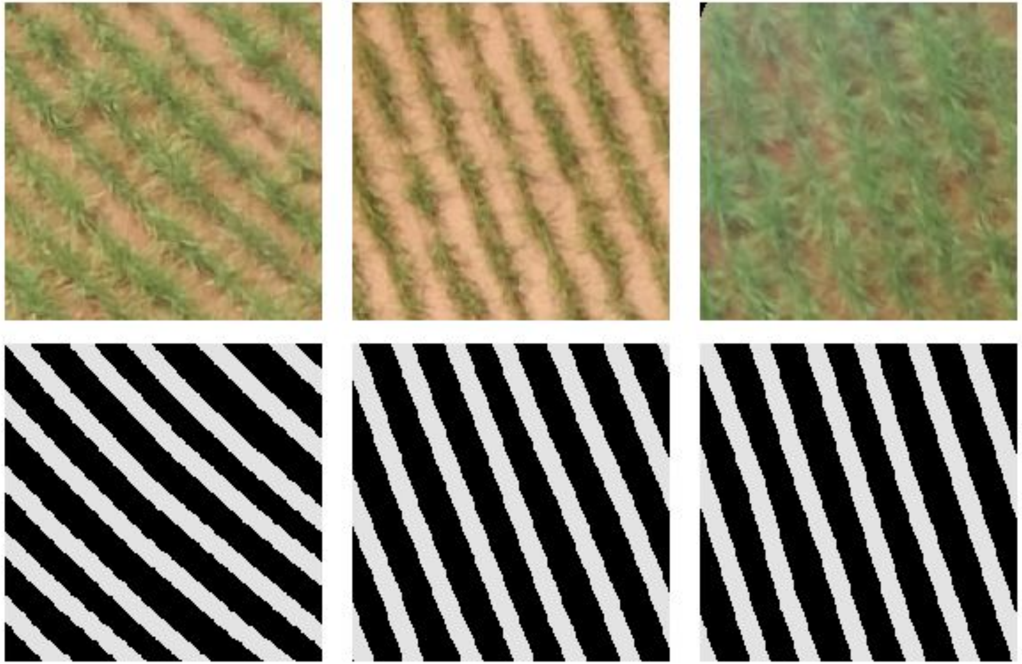


Figure: Examples of crop lines and the segmentation provided by an expert

Evaluation metrics

- Dice Similarity Coefficient (DSC):

$$D = 2\frac{|A \cap B|}{|A| + |B|}$$

- Jaccard Similarity Coefficient (JSC):

$$J(A,B) = 1 - \frac{|A \cap B|}{|A \cup B|} = 1 - \frac{|A \cap B|}{|A| + |B| - |A \cap B|}$$

Evaluation metrics

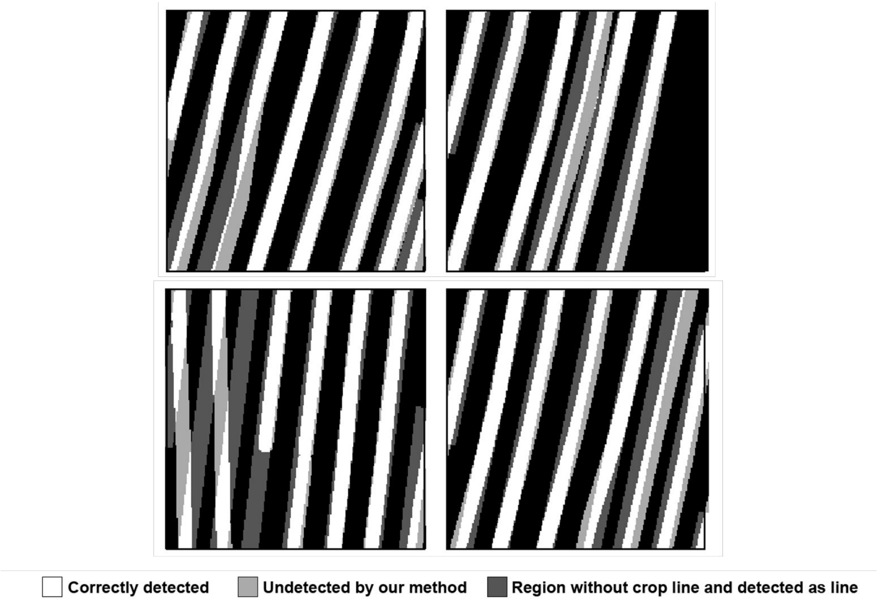
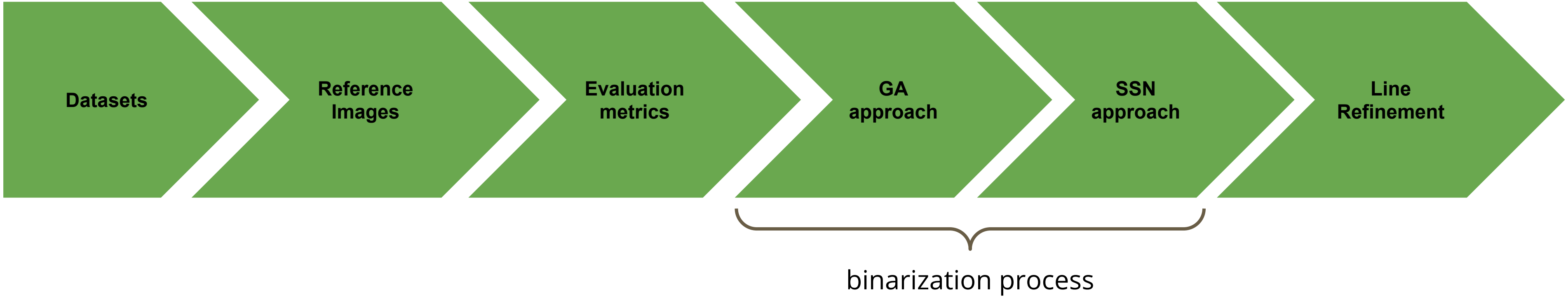


Figure: Visual representation of crop row evaluations.

Methodology Flux



Segmentation using Genetic Algorithm

- 2700 generations, population 200 individuals;
- Mutation rate of 0.05 and crossover rate of 0.8;
- 35 training images of sugarcane crops with sizes from 450 to 1136 pixels;
- Different ages and width of cane extracted from the 4 test maps;
- DSC to compare results.

Segmentation using Genetic Algorithm

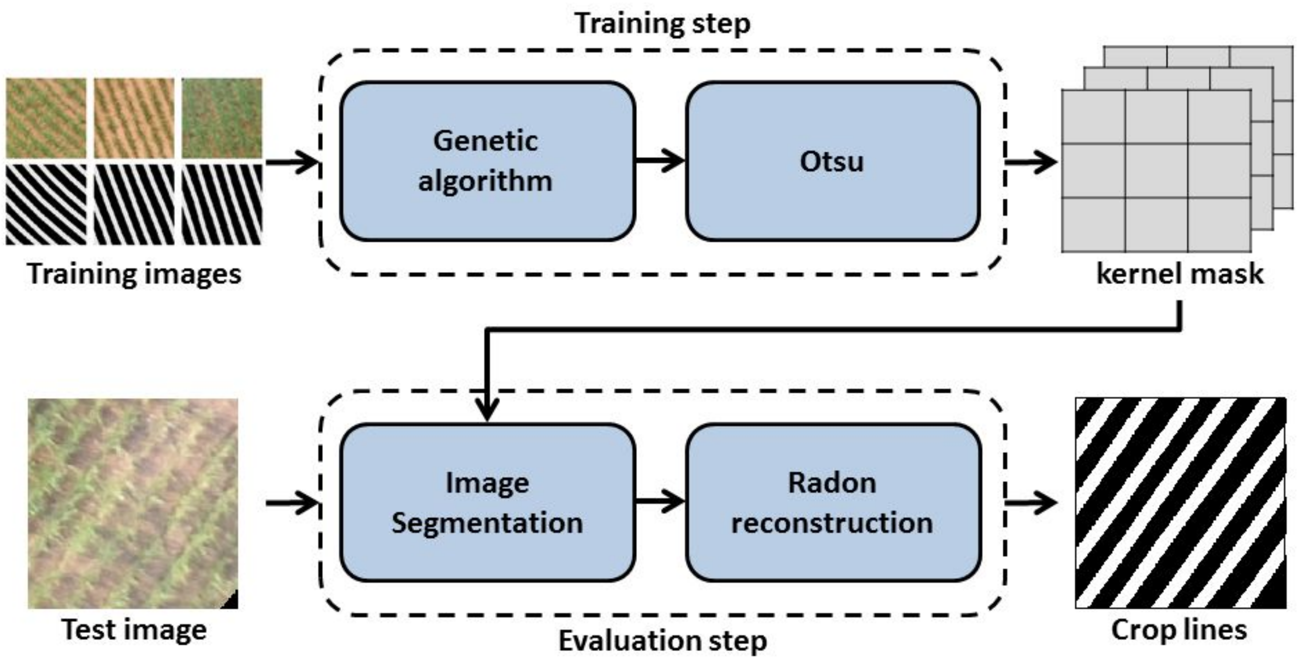


Figure: Flow chart of the first approach based on Genetic Algorithm and Radon transform.

Semantic Segmentation Network

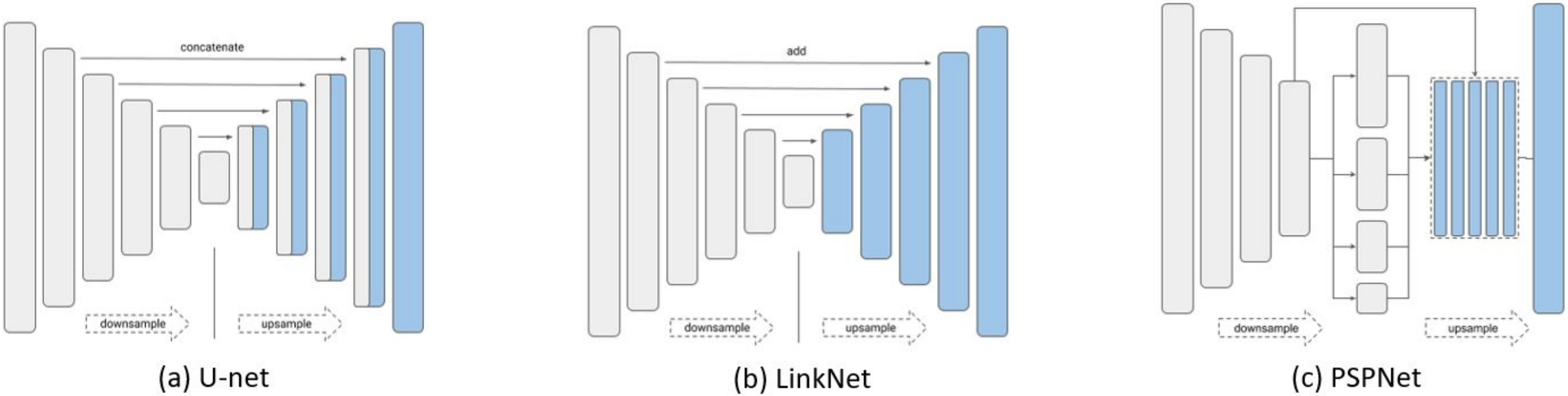
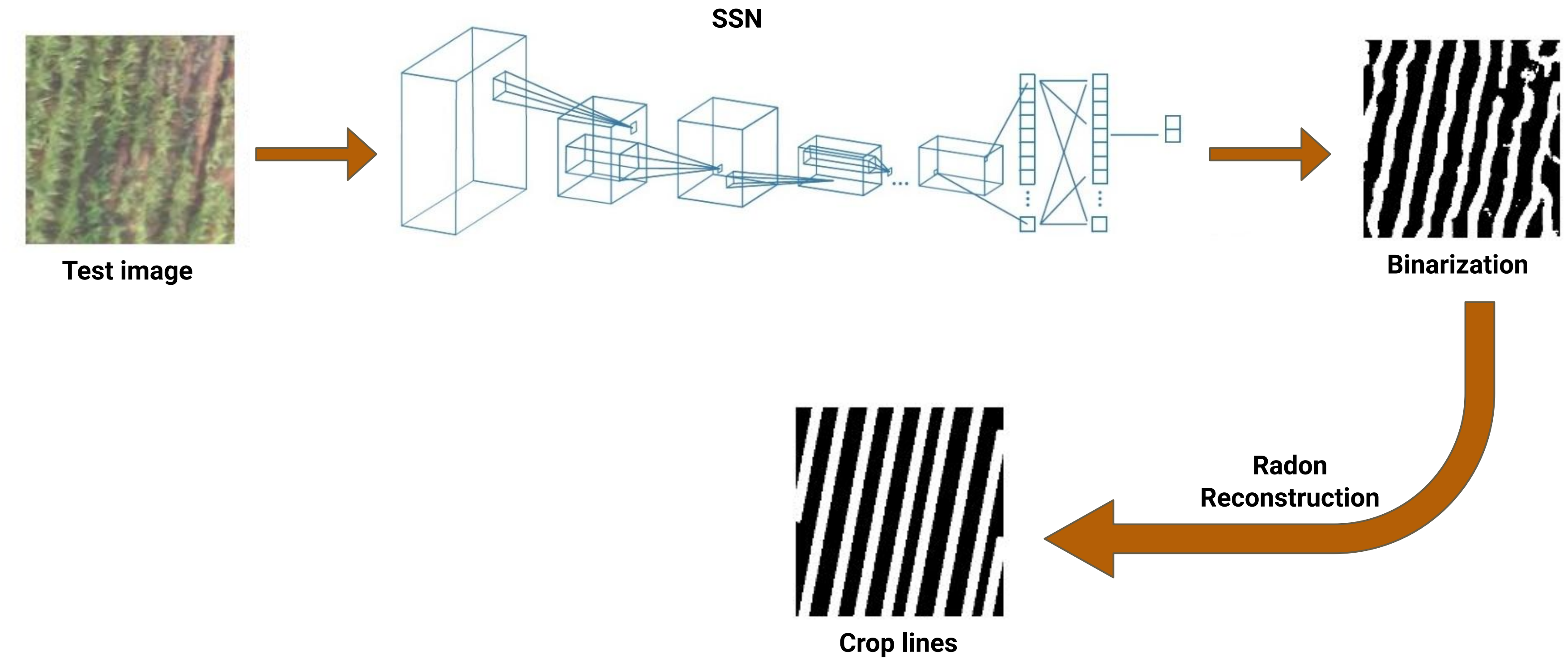


Figure: Architectures used for semantic segmentation. Adapted from (YAKUBOVSKIY, 2019).

Semantic Segmentation Network



Semantic Segmentation Network

- CNN training with dataset A;
- Crops of 256×256 pixels, with 256 pixels of stride;
- Only areas with at least 80% of useful information were considered;
- Data augmentation methods: rotations, translations, scaling and shearing;
- 0.001 learning rate for 50 epochs;

Line Reconstruction and Refinement

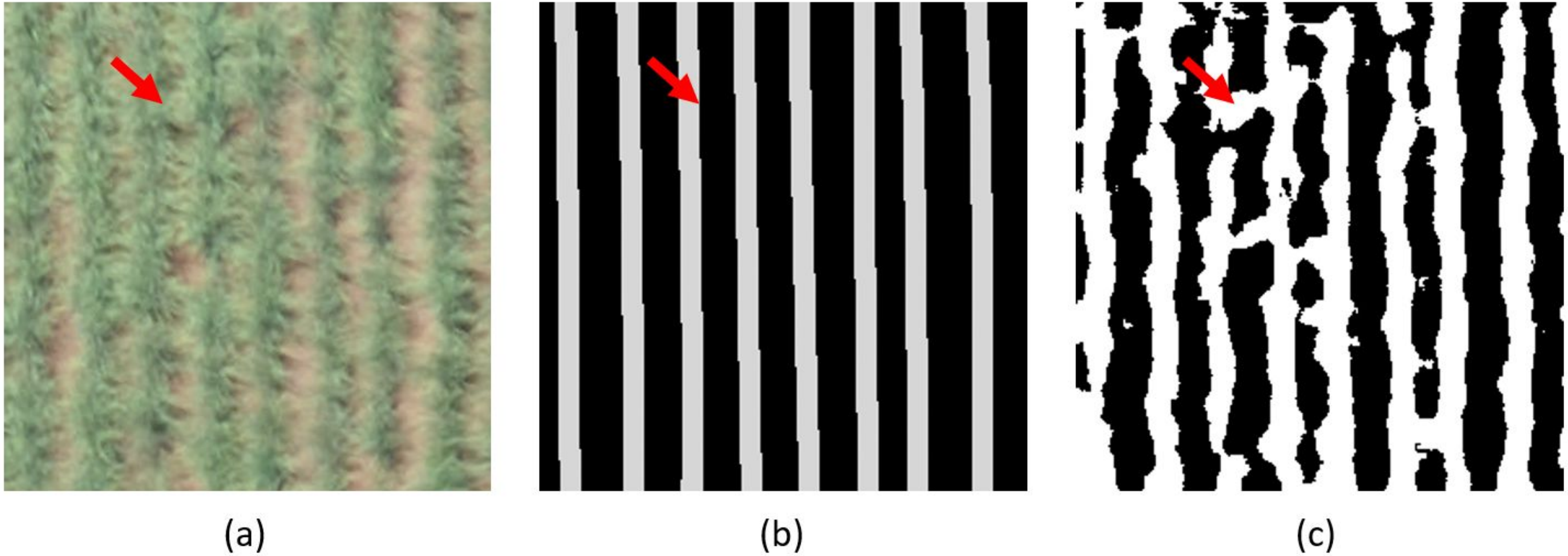


Figure: Problems encountered after the segmentation step: (a) Original image; (b) Planting lines provided by an expert; (c) Image after segmentation.

Line Reconstruction and Refinement

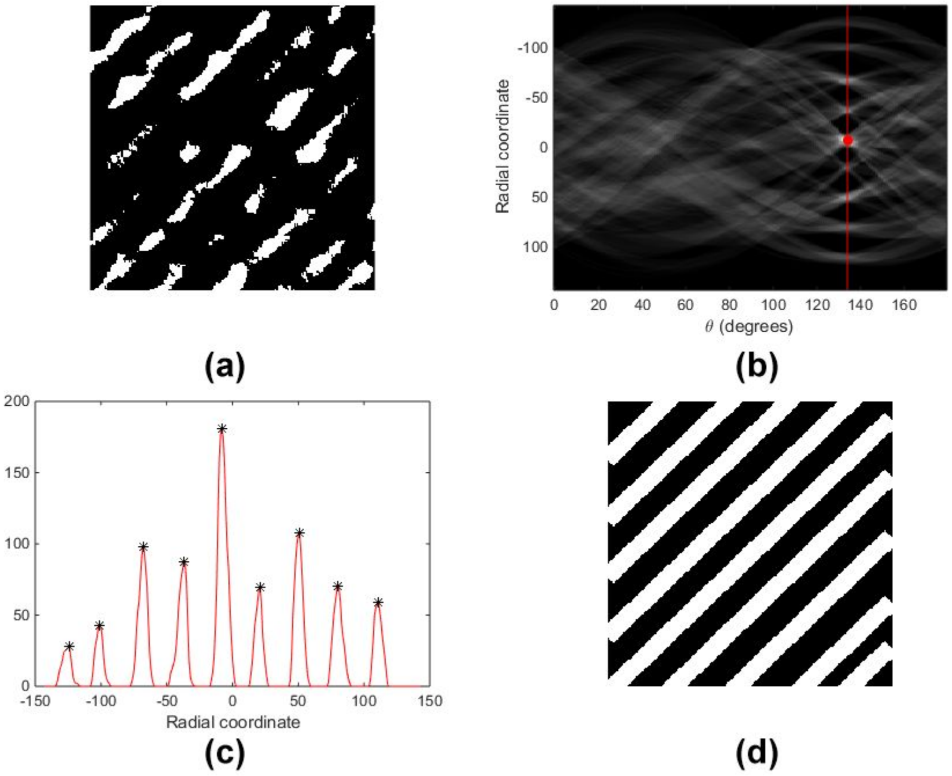


Figure: Proposed scheme for crop line reconstruction using Radon transform: (a) Input image; (b) Matrix obtained with the Radon transform. The red dot represents the location of the maximum point and the orientation angle of the input image; (c) Radon transform obtained for the image orientation angle (red line in (b)). Each peak of the curve corresponds to the center of aline in the input image; (d) Reconstruction of the lines using the orientation angle and the peaks of the Radon transform for that angle.

5.Experimental Results

Segmentation using Genetic Algorithm

- We applied a K-fold evaluation (5 folds) as GA is stochastic;
- Different thresholds (local and global);
- Different stride and windows values for the local threshold.

Segmentation using Genetic Algorithm

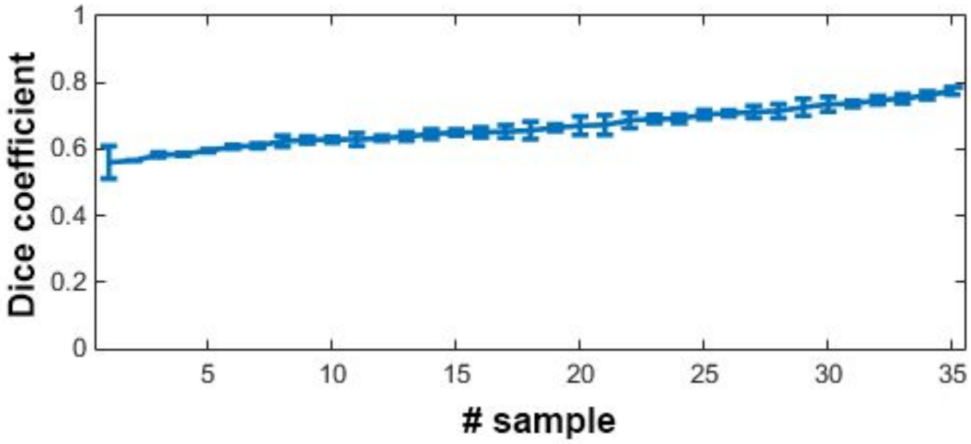


Figure: Average Dice coefficient and standard deviation for different images for 5 different GA kernel masks.

Segmentation using Genetic Algorithm

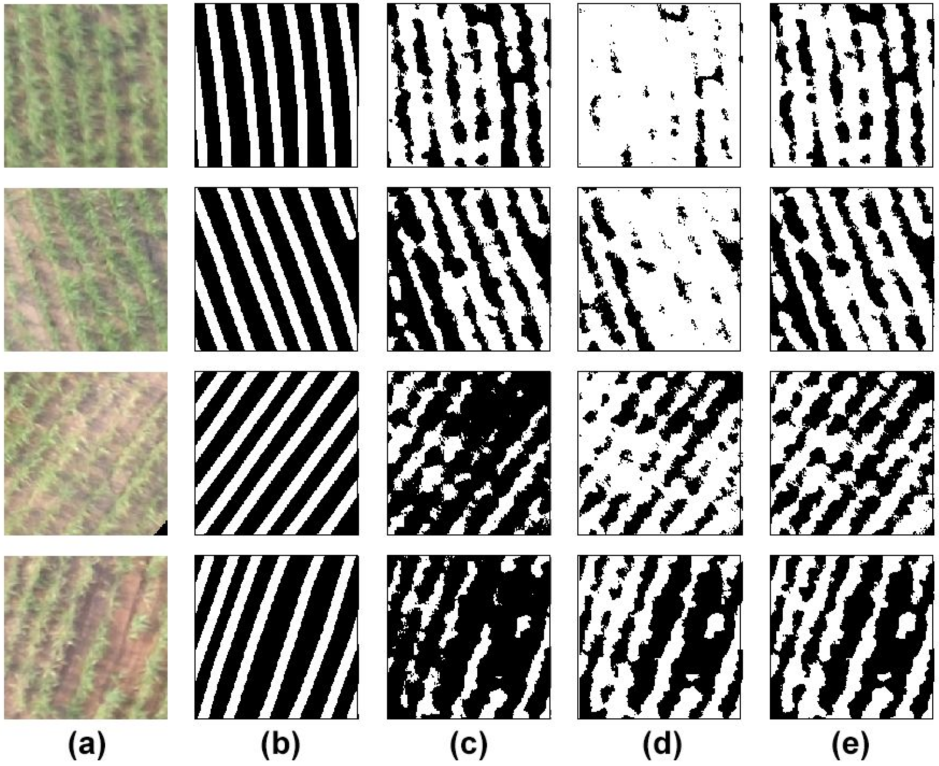


Figure: Results for different sections of the map: (a) Original image; (b) Expert's segmentation; (c) Manual threshold (t= 0.8); (d) Global Otsu; (e) Local Otsu (W= 50 and S= 25).

Segmentation using Genetic Algorithm

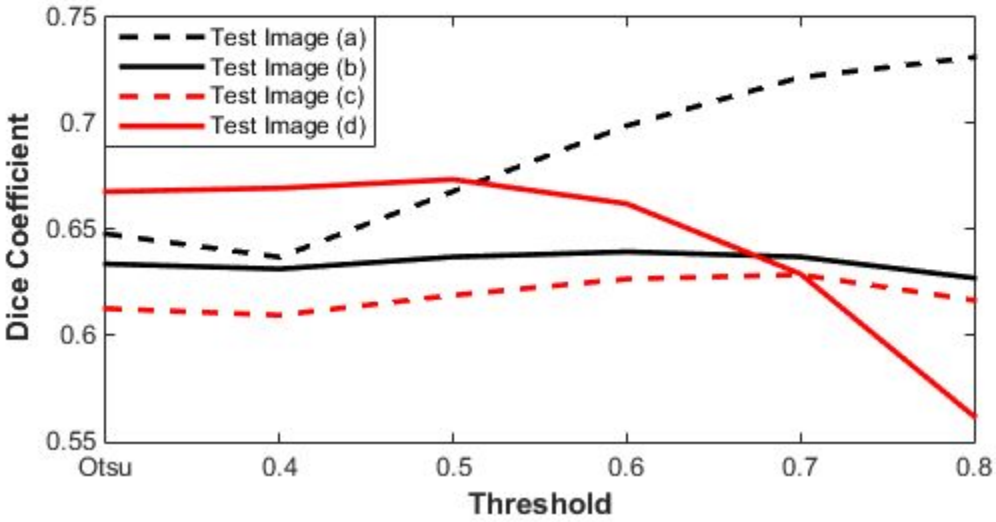


Figure: Dice coefficient for various global threshold values.

Segmentation using Genetic Algorithm

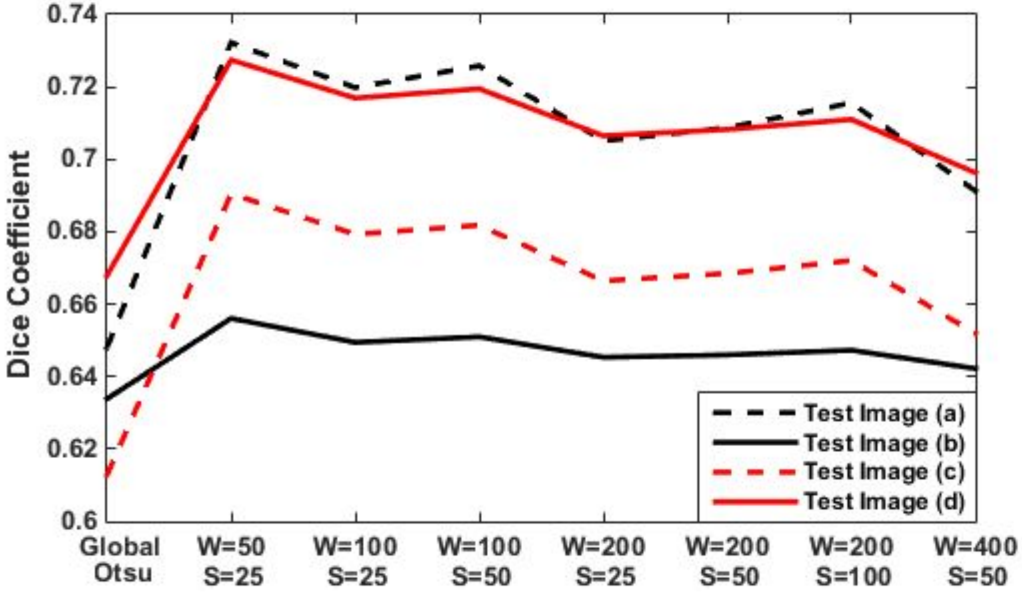


Figure: Dice coefficient obtained using Global Otsu and Local Otsu for different combinations of Window W and Stride S.

Segmentation using Genetic Algorithm

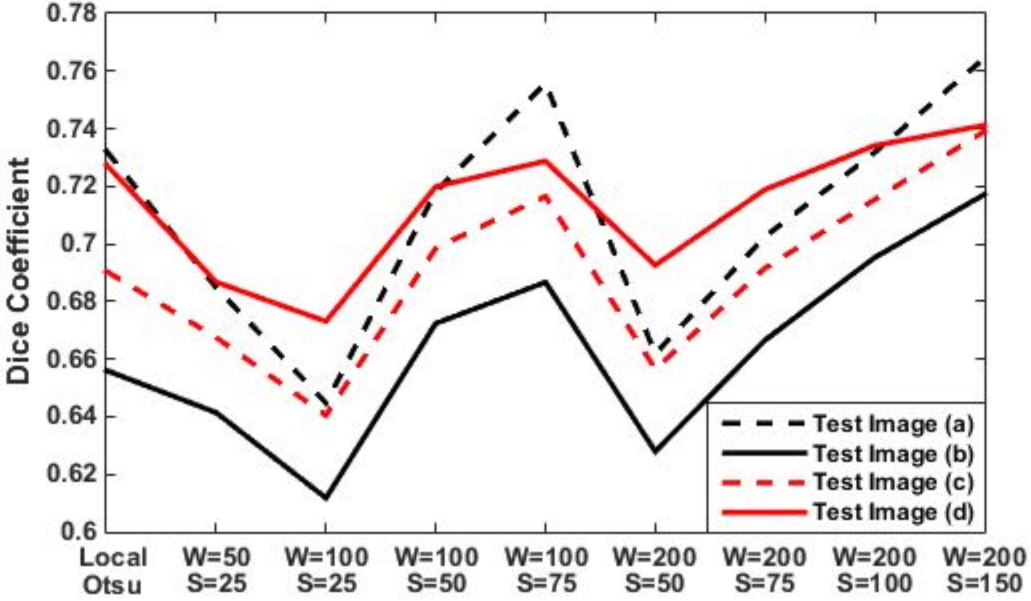


Figure: Dice coefficient obtained for the line reconstruction for different combinations of Window W and Stride S.

Semantic Segmentation

- We applied a K-fold evaluation (10 folds);
- Datasets A, B, C, and D, with 678, 3291, 1550 and 2162 images respectively;
- We experimented the classification of dataset A with the three SSNs;

Semantic Segmentation

Segmentation Network	Dice Coefficient
VGG16 - LinkNet	0.90 ± 0.0062
VGG16 - PSPNet	0.88 ± 0.0075
VGG16 - Unet	0.87 ± 0.0113

Table: Segmentation results obtained with the application of the segmentation net-works in Dataset A.

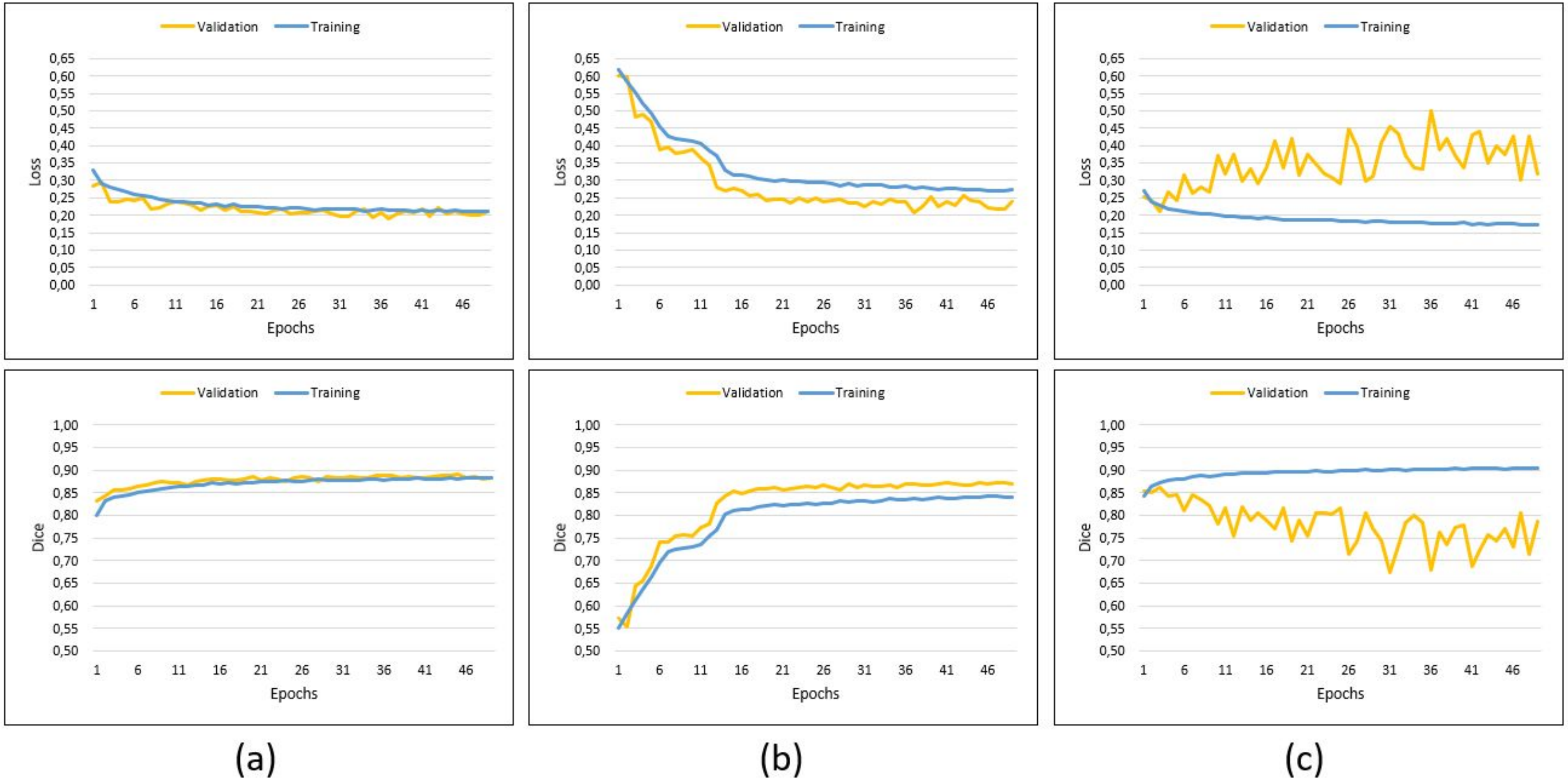


Figure: Results obtained for each segmentation networks. Top row shows the loss function, while the bottom row shows the Dice coefficient: (a) LinkNet (b) PSPNet and (c) U-net.

Semantic Segmentation

Dataset	Dice Coefficient
A	0.90 ± 0.0062
B	0.80 ± 0.0702
C	0.84 ± 0.0724
D	0.86 ± 0.0588

Table: Result obtained with the application of the LinkNet network trained in dataset A to segment other datasets.

Semantic Segmentation

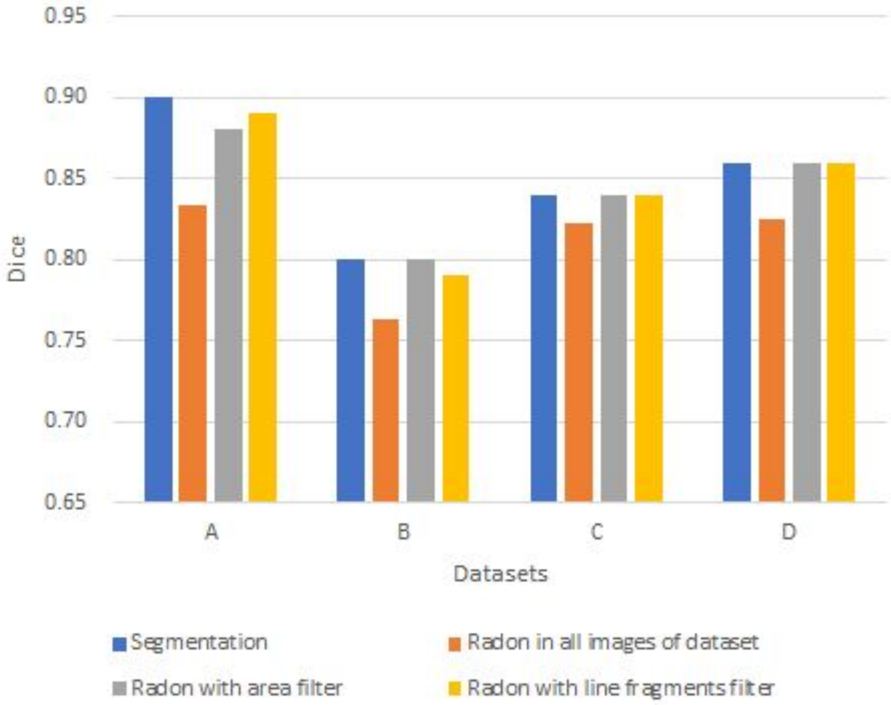


Figure: Average Dice coefficient obtained for different selection approaches during the crop line reconstruction.

Semantic Segmentation

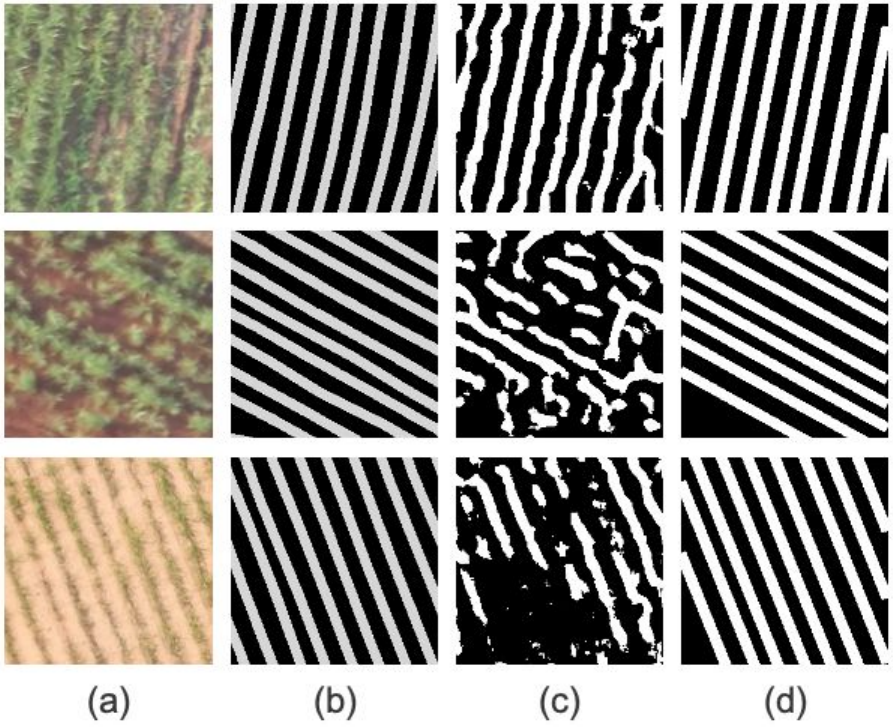


Figure: Examples of images where there was an improvement in the Dice coefficients after line reconstruction using the Radon transform. (a) Original image;(b) Segmentation provided by the expert; (c) Segmentation obtained using LinkNet; (d) Line reconstructed

Semantic Segmentation

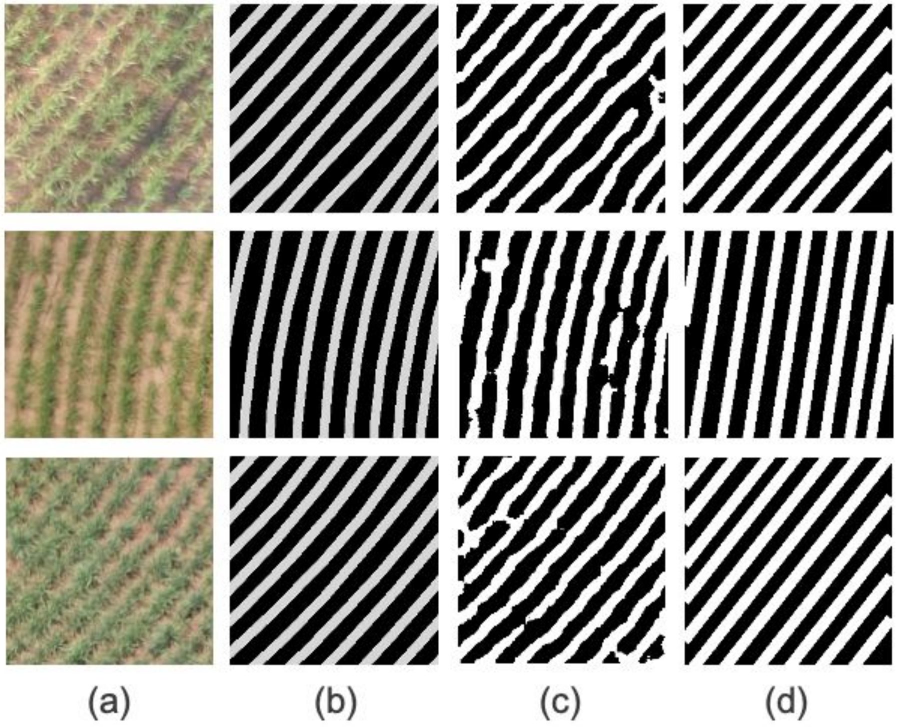


Figure: Examples of images where there was a decrease in the Dice coefficients afterline reconstruction using the Radon transform. (a) Original image; (b) Segmentation provided by the expert; (c) Segmentation obtained using LinkNet;(d) Line reconstructed.

Comparison of approaches

- Genetic Algorithm based technique:
    - requires less training images than Semantic Segmentation;
    - used only 27 parameters (3x3x3 kernel mask) to optimize the training, while SSN used millions;
    - showed a better DSC with local Otsu threshold not reaching 0.78 versus 0.90 from SSN.

Comparison of approaches

- SNN based technique:
  - much more constant Dice coefficient;
  - manages to extract several different levels of abstraction, each of these levels focusing on a different type of feature, such as border, texture, etc;
  - tends to be more capable of operating in different stages of the crop regardless of color contrast;

6. Conclusions

Conclusion

- Methodology to segment crop lines from UAV images:
    - Genetic Algorithm approach associated with Otsu method;
    - A new approach based on LinkNet SSN to perform the segmentation step;
- Line reconstruction approach based on the Radon transform;
- Results indicate that our SSN approach is a feasible solution to the problem.

Main Contributions

- Helps spread the use of geolocation and autonomous vehicles in crops;
- More efficient application of inputs;
- Better efficiency of the land area;
- Reduction in the production coast;
- Increase of profits based on non-perennial harvests;
- Considerable less aggression to the environment.

Contributions in Bibliographic Production

- Submitted papers:
  - SILVA, R. R.; ESCARPINATI, M. C. and BACKES, A. R. **Sugarcane CropLine Detection From UAV Images Using Genetic Algorithm and Radon Transform**. Submitted to Signal, Image and Video Processing manuscript;
  - SILVA, R. R.; DIAS JR., J. D.; ESCARPINATI, M. C. and BACKES, A.R. **Detection of sugarcane crop line from UAV images using Semantic Segmentation and Radon Transform**. Submitted to Computers and Electronics in Agriculture;

Contributions in Bibliographic Production

- SILVA, R. R.; BRITO, L. F. A.; ALBERTINI, M. K.; NASCIMENTO, M. Z.and BACKES, A. R. **Using CNNs for Quality Assessment of No-Reference and Full-Reference Compressed-Video Frames**. In: XVI WORKSHOP DE VISÃOCOMPUTACIONAL, 2020, Uberlândia. Anais do 16◦Workshop de Visão Computacional, 2020;

- This work is currently running for the Mercosur Science and Technology Award:
  - SILVA, R. R.; DIAS JR., J. D.; ESCARPINATI, M. C. and BACKES, A.R. **Detecção de linha de plantio de cana de açúcar a partir de imagens de VANT usando Segmentação Semântica e Transformada de Radon**. Submitted to Prêmio Mercosul de Ciência e Tecnologia – edição 2020.

Future Work

The results obtained by this work demonstrate the good performance obtained by the proposed approach and motivate new lines of investigation, such as:

- Evaluation of datasets of different cultures besides sugar cane;
- Explore how mosaic alignment techniques interfere in the result;
- Explore the use of other sensors in association with the images to produce better results;
- Study new methods to enhance crop reconstruction of regions with highly-curved lines.

Thanks!

Questions and Discussions