SEVENTH FRAMEWORK PROGRAMME

Robust pixel-based classification of obstacles for robotic harvesting of sweet-pepper

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CROPS "Clever Robots for Crops"

Overview

- Explanation about CROPS project
- Article

EU project CROPS

- Web page: www.crops-robots.eu

- 14 partners from 10 countries develop:
  - Harvesting robots for apple, grape and sweet-pepper
  - Spraying robot for apple and grape
  - Detection of trees for forestry

The team

Wageningen UR deals with sweet-pepper harvesting

- State of the project
  - We are in 3rd year
  - Currently integrating vision and arm control
  - Basic field test scheduled in July 2013
  - Large field test scheduled in 2014

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Video of manipulator moving to fruit

PhD research

- Thesis topic:

  Development of a harvesting robot for sweet-pepper

- Objectives:
  - 1. Literature review of harvesting robots in high-value crops
  - **2. Localization of hard (stem) and soft (leafs) obstacles**
  - 3. Collision-free detachment of the fruit
  - 4. Field tests with the harvesting robot

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2^{nd} Part: Article

- Title: Robust pixel-based classification of obstacles for robotic harvesting of sweet-pepper

Article is in: Computers and Electronics in Agriculture 96: p. 148-162

http://www.sciencedirect.com/science/article/pii/S0168169913001099

Obstacles classification for robotic harvesting, why?

Motion planning tough → requires loc. of obstacles

<u>Group of 4 peppers in a range of 1 m</u>

'Take home' messages of paper

- Obstacle detection for fruit harvesting hardly studied, most work focused only on fruit detection
- First study with quantitative performance, other studies reported performance only qualitatively
- Images recorded under varying lighting conditions
- New performance measure P_{rob} → consistent class.
- Multi-spectral is limited to detect plant parts

1. Introduction

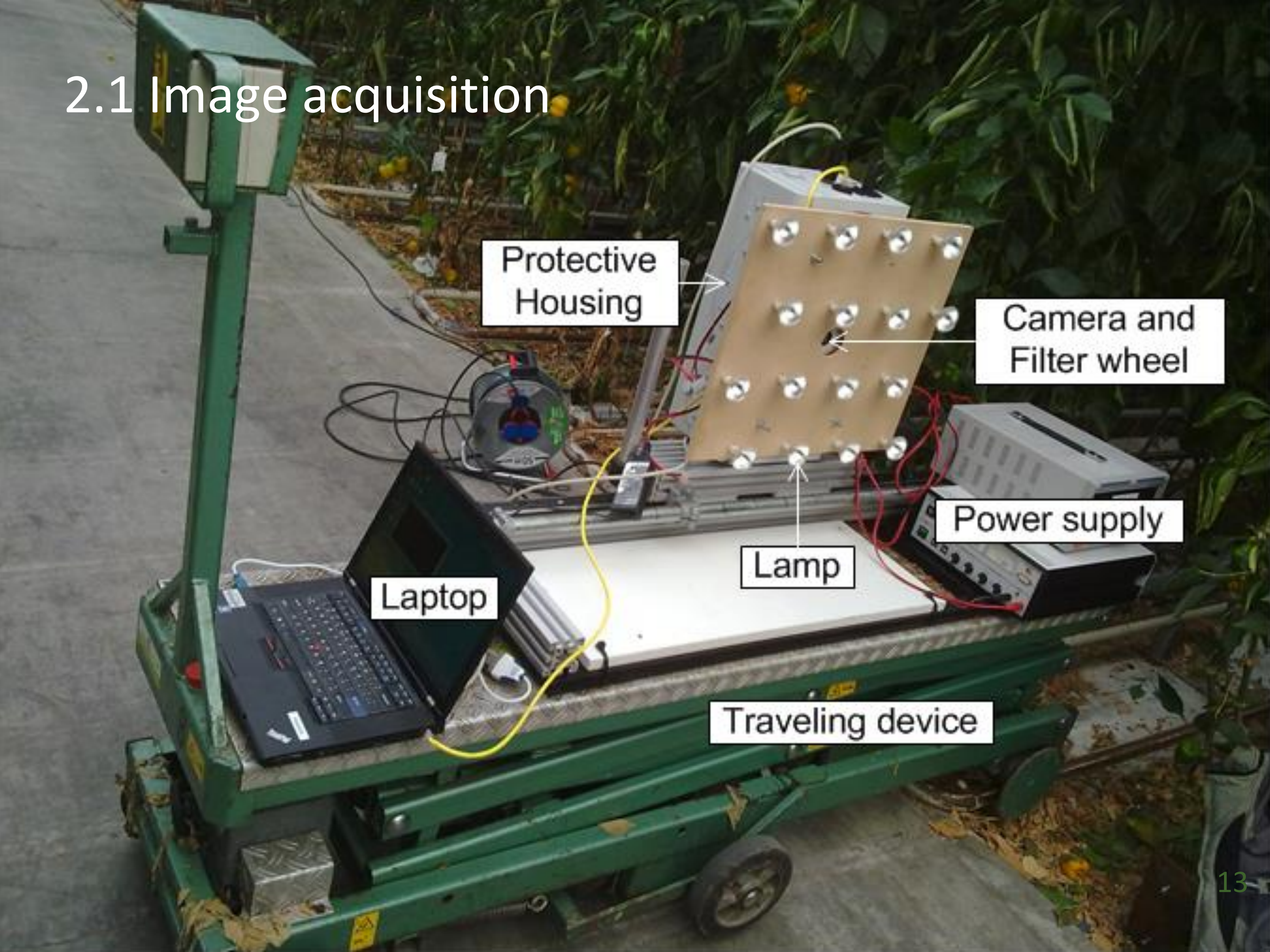
- Hard obstacles should be avoided and soft obstacles can be pushed aside by a robot arm
- Related work
  - Cucumber stem, leaf and fruit (Van Henten, 2006; Noble, 2012)
  - Branches of citrus (Lu et al. 2011)
  - Stems of Lychee (Deng et al. 2011)
  - Branches and leaves of Grapes (Dey et al. 2012)

  → All lack quantitative performance

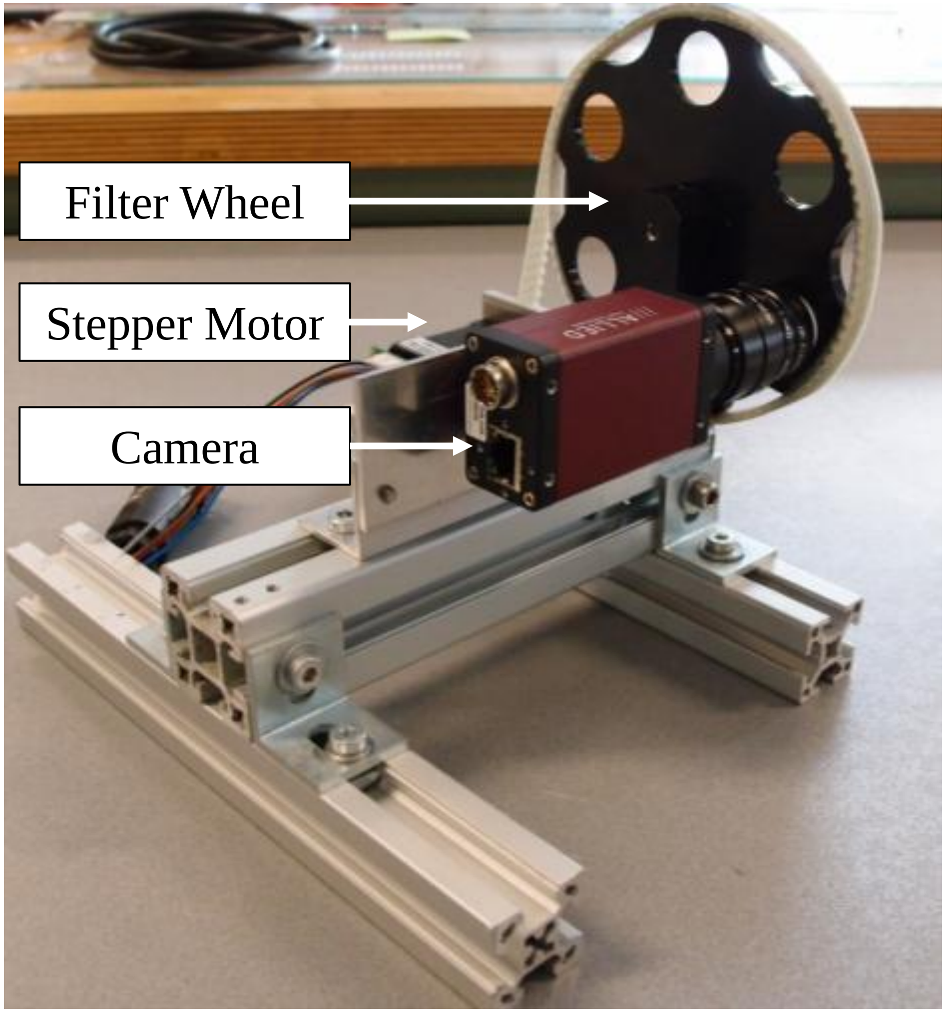
1. Introduction

- Objectives
  - (1) detect plant vegetation
  - (2) segment non-vegetation objects;
  - (3) prune a decision tree and select features such that the classifier is robust to variation among scenes;
  - (4) classify hard and soft obstacles →stems, top of leaves, bottom of leaves, green fruits and petioles.

2.1 Image acquisition



Multi-spectral camera



- Set-up
  - Filter wheel (Edmund Optics)
  - 6 (Ø25 mm) 40nm BP Filters
  - AVT Manta G-504 Monochrome camera; 5 MP (Allied Vision Technologies)
  - Halogen lighting

Camera to stem distance ≈ 50 cm

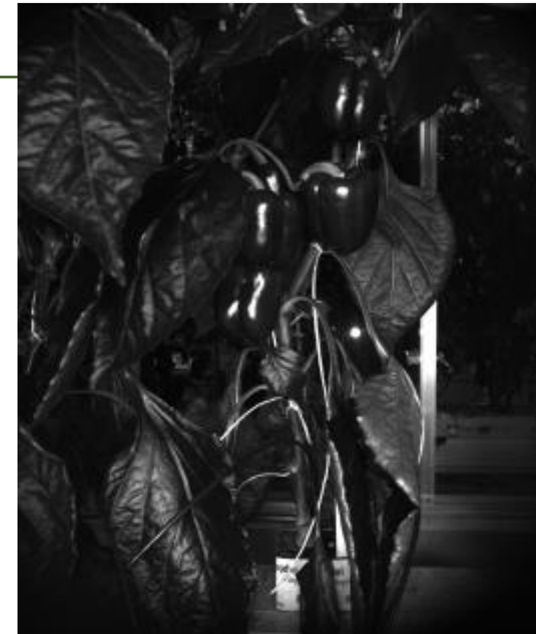
Data

- Data
  - 12 scenes during sunny day in Wageningen
  - Cultivar: Viper (Red)
  - 6 wavelengths per pixel

447 nm

562 nm

624 nm

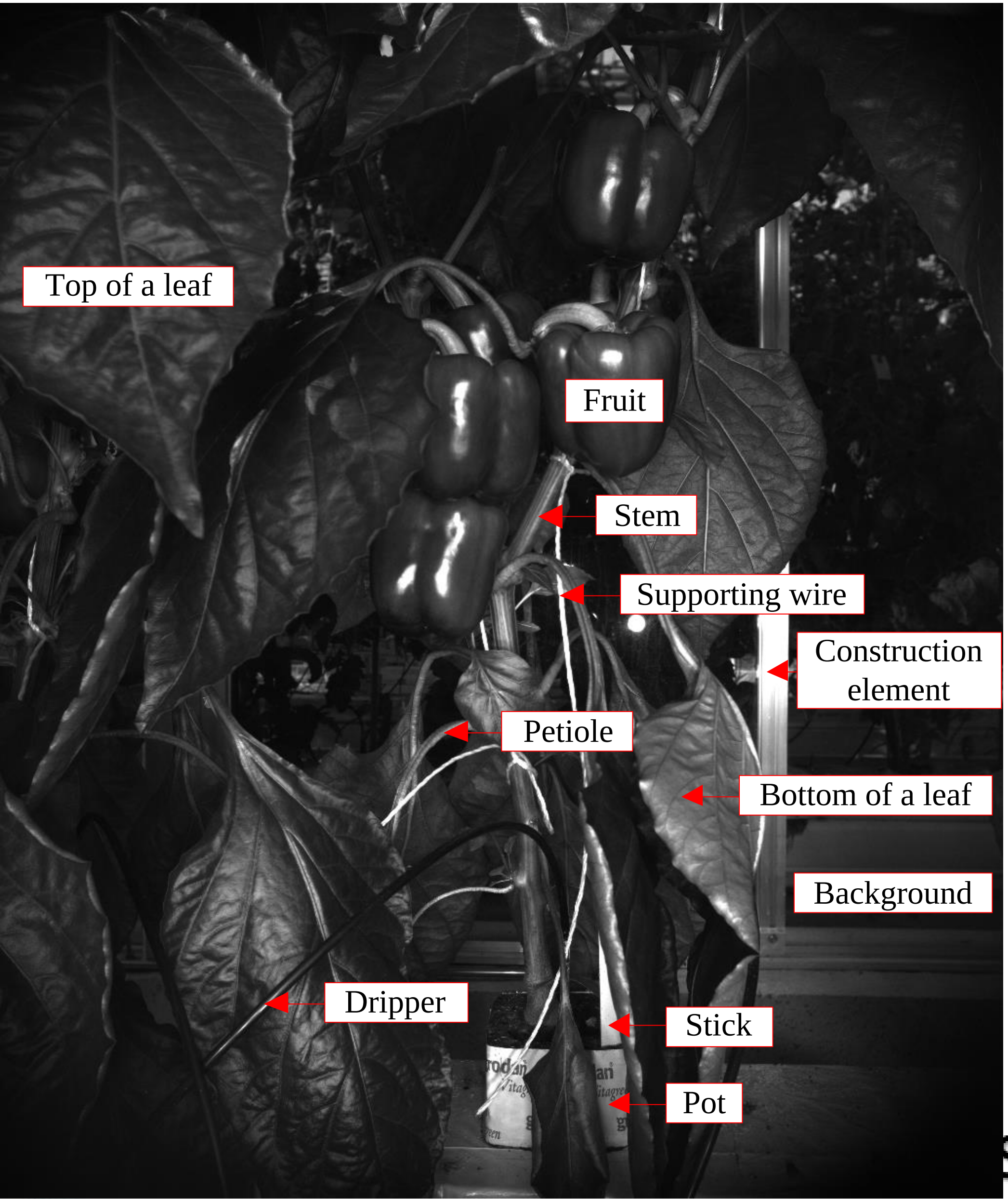


692 nm

716 nm

>900 nm

9 Objects occur in a scene



Object type	Classified for motion planning as
Objects with distance >1 m	Background
Unknown	Background
Supporting wire	Hard obstacle
Stick, dripper and pot	Hard obstacle
Construction elements	Hard obstacle
Stem	Hard obstacle
Petiole	Soft obstacle
Top of a leaf	Soft obstacle
Bottom of a leaf	Soft obstacle
Fruit	Target (ripe) or hard obstacle (unripe)

2.3 Background segmentation

Useful property: Solar irradiance drops at 925-975 nm

2.4 Segmentation of overexposed regions

Blue → hard obstacle, if area => 300 pixels

Red → background, if area < 300 pixels

3.1 Performance measure

Table 2
Confusion matrix.

		Actual class	
		Object I	Object II
Classified class	Object I	TP_I	FP_I
	Object II	FP_{II}	TP_{II}

$$TPR2(I) = \frac{100 \cdot TP_I}{TP_I + FP_{II}} \ (\%)$$

$$TPR2(II) = \frac{100 \cdot TP_{II}}{TP_{II} + FP_I} \ (\%)$$

3.1 Performance measures

- Balanced accuracy (for one scene)

$$Acc2_{Bal} = 0.5 \cdot (TPR2(I) + TPR2(II)) \ (\%)$$

- NEW: Robust-and-balanced accuracy (for several scenes)

$$P_{Rob} = \frac{Rob_{Mit} \cdot 0.5 \cdot (M_{TPR2(I)} + M_{TPR2(II)})}{0.5 \cdot (SD_{TPR2(I)} + SD_{TPR2(II)}) + Rob_{Mit}} \ (-)$$

- Rob_{Mit} is ‘weighting factor’ for robustness vs. accuracy

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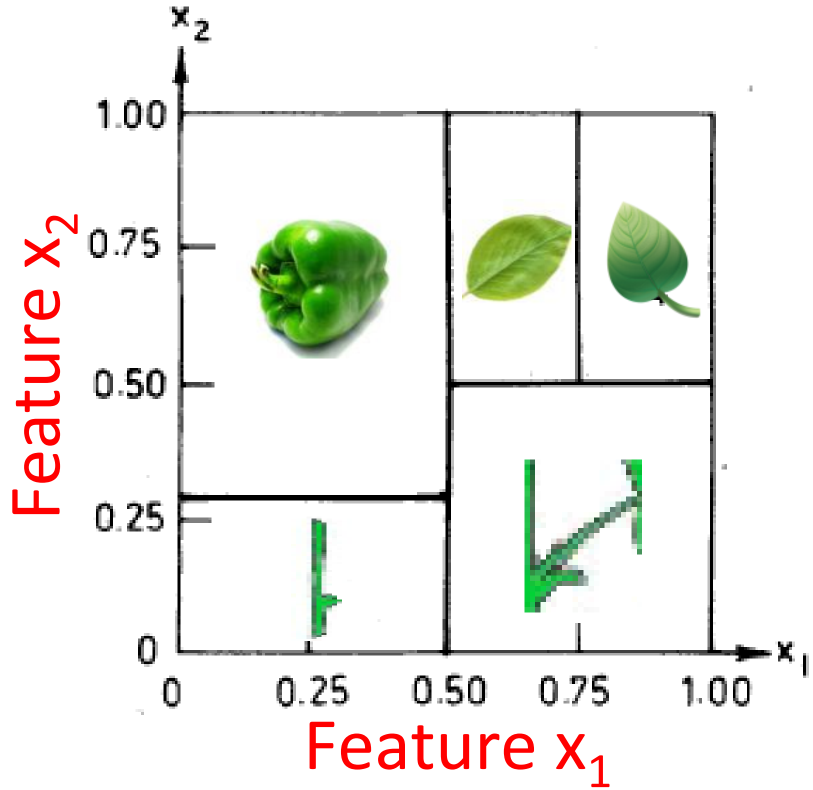
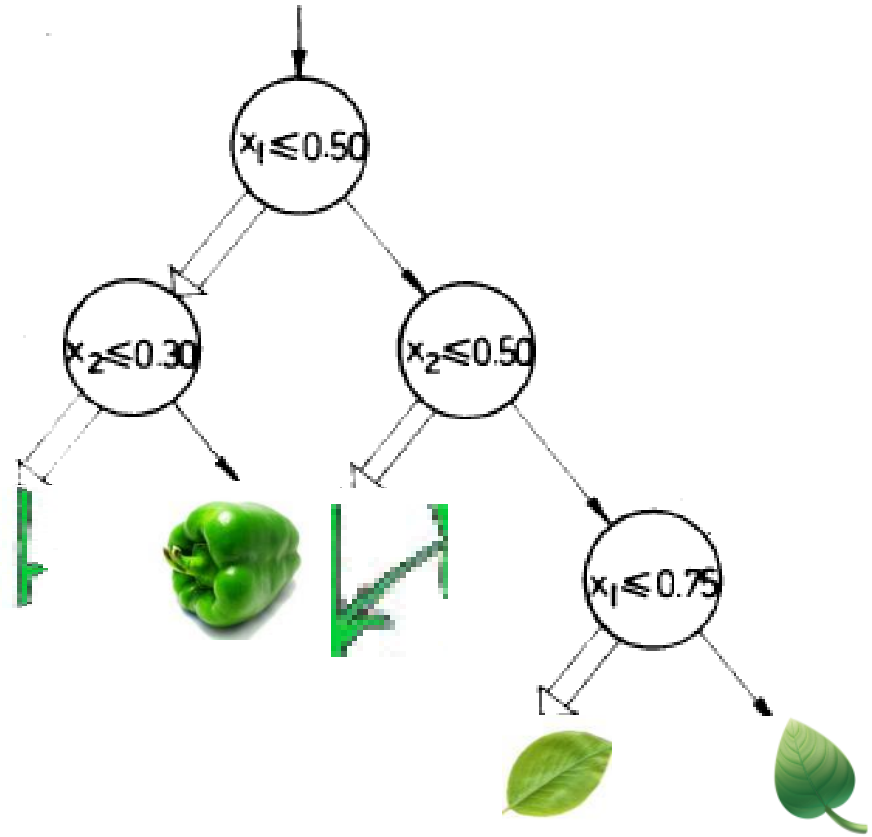
3.2-3.4 Classifier and features

- Classifier: CART decision tree (Breiman, 1984), in Matlab
- Feature selection algorithm: SFFS (Pudil, 1994)
- Pixel-based features
  - Raw data
  - Entropy
  - Normalized Difference Index (NDI)
  - Spectral Angle Mapper (SAM)
  - Mahalanobis Distance

Decision tree, how does it work?

Source: (Sethi and Sarvarayudu, 1982)

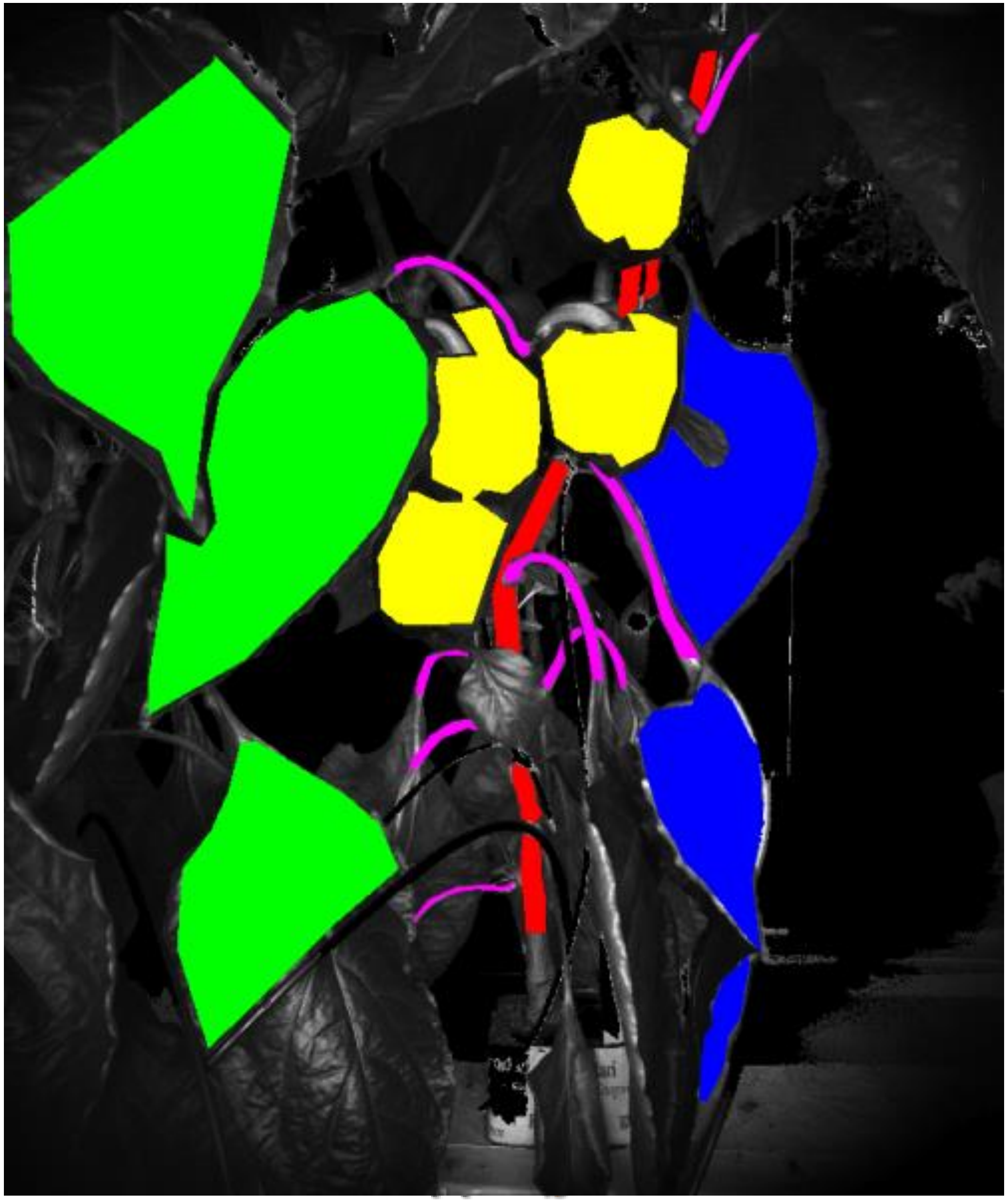




4. Experiments

- Experiment 1: Evaluation of classifier robustness
- Experiment 2:
  - a. Separability for each binary combination of plant parts
  - b. Derive approach to classify 5 plant parts
  - c. Select features
  - d. Evaluate performance

4.1 Ground truth: drew 5 classes (stem, TL, BL, fruit, pet)



4.2 Training and testing data

- 2 scenes for training
- 10 scenes for testing

Results

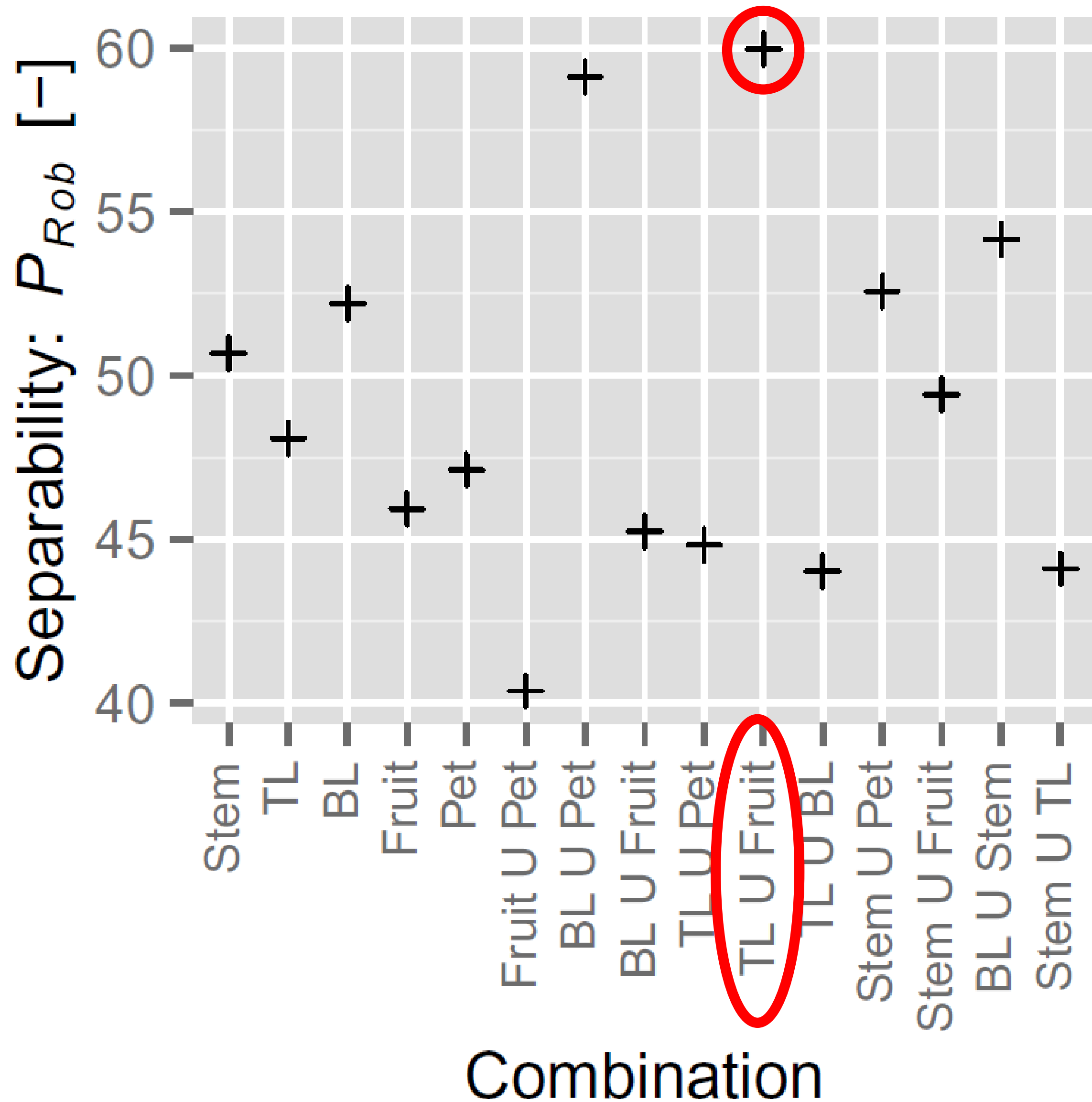
5.1 Comparison of performance measures

	Performance measure used	
	Balanced accuracy: $Acc2_{Bal}$	Robust-and-balanced accuracy: P_{Rob}
Features (NDI spectral) in the pruned decision tree; ordered on occurrence.	562&900; 692&716; 692&900; 562&716; 624&692; 562&624	447&624; 624&900; 692&716; 562&624
Balanced accuracy $Acc2_{Bal}$ (%)	77.1	75.4
$M_{TPR2(hard)}(SD_{TPR2(hard)})$ (%)	66.5 (17.2)	59.2 (7.1)
$M_{TPR2(soft)}(SD_{TPR2(soft)})$ (%)	87.4 (7.0)	91.5 (4.0)

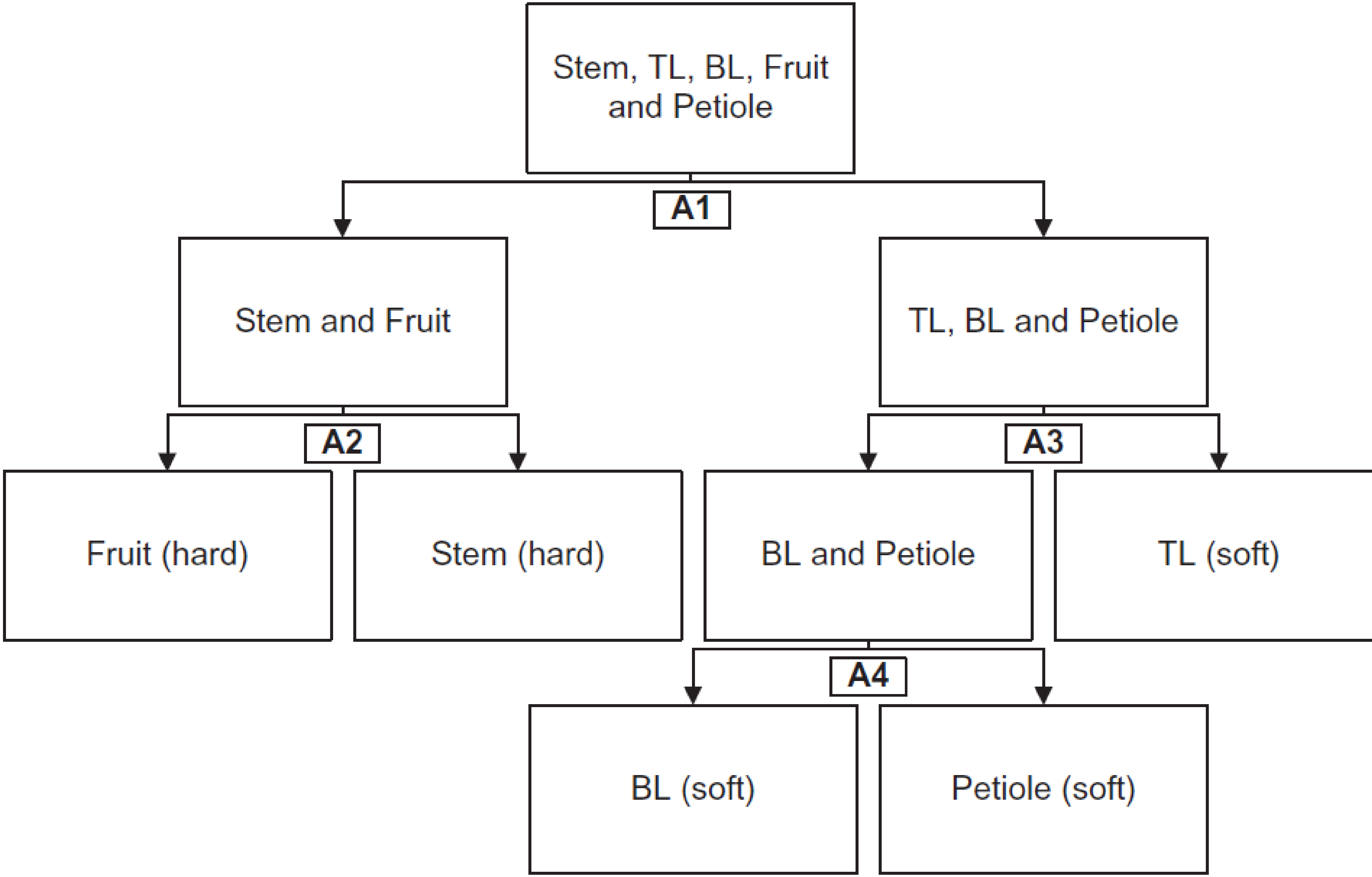
Reduction of 2%

Reduction of ± 50%

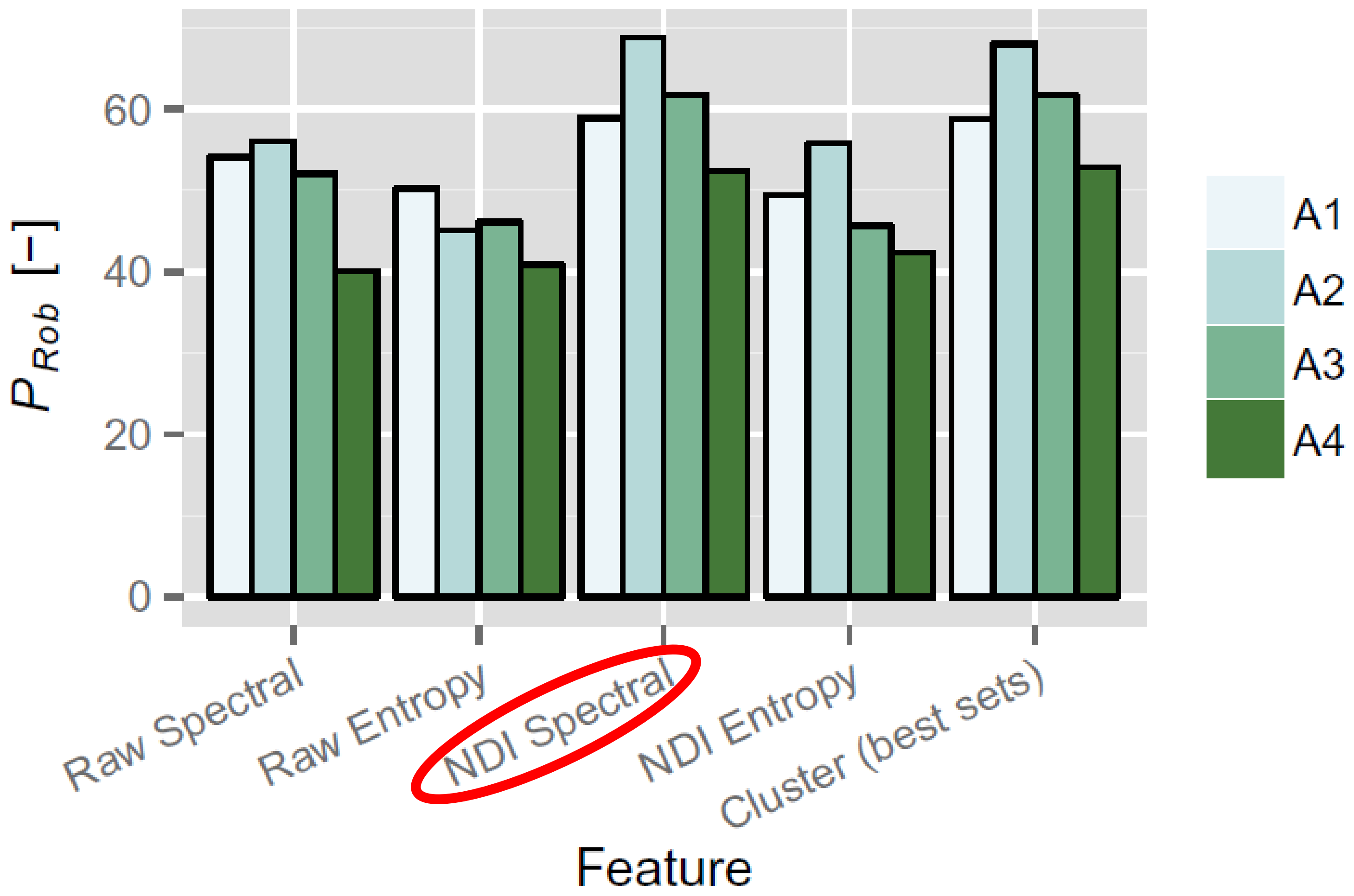
Separability for 15 binary combinations of plant parts



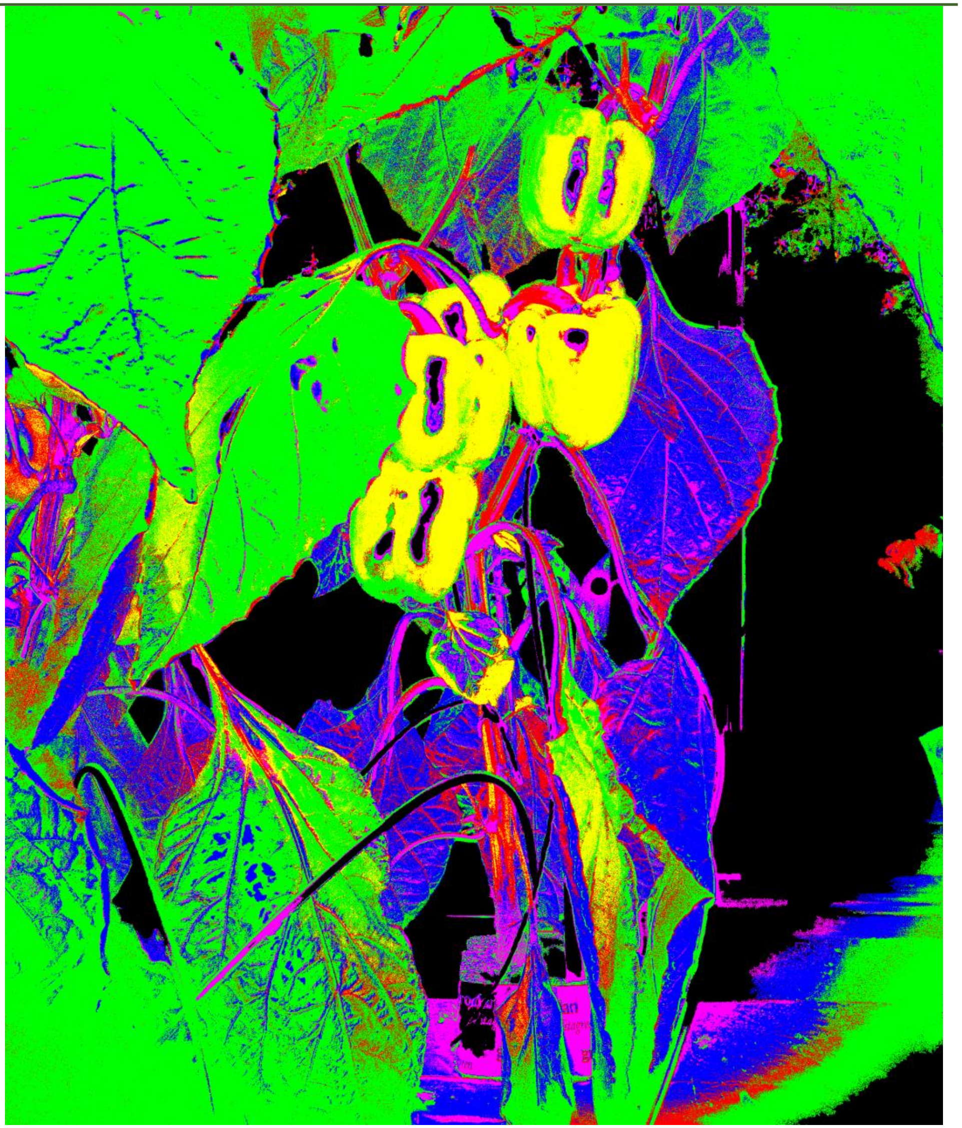
5.5 Approach to classify 5 plant parts



5.6 Performance per binary problem A1-A4



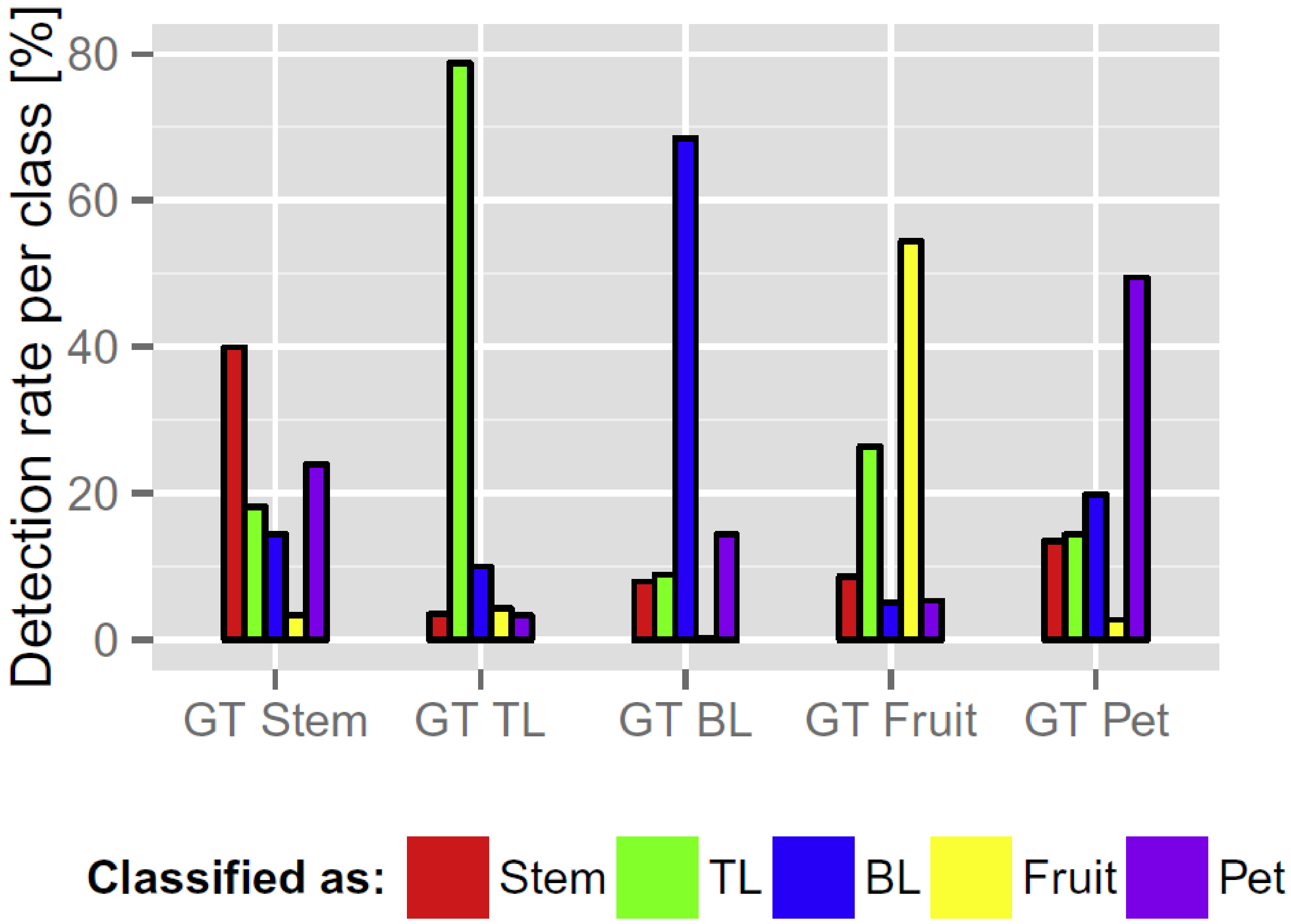
5.8 Result of classification into 5 classes



Mean true-positive detection rate

- Stem: 40%
- TL: 79%
- BL: 69%
- Fruit: 55%
- Petiole: 50%

False positives



Discussion

- Two possible causes for low performance
  - Varying camera-object distances
  - Natural lighting varied during recording
- Possible solutions
  - Use of a reference card
  - Use of distance information
  - Addition of object-based features

Conclusion

- Performance too low for a reliable obstacle map for motion planning
- Mean TPR (SD)
  - Hard obstacles: 59.2 (7.1)%
  - Soft obstacles: 91.5 (4.0)%
- P_{Rob} renders classifier more robust to variation among scenes
- First study with quantitative results of obstacle detection for fruit harvesting

Thank you!!!

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