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

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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
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
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
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
Obstacles classification for robotic harvesting, why?

Motion planning tough → requires loc. of obstacles

Group of 4 peppers in a range of 1 m
‘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 $P_{rob} \rightarrow$ 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

- 12 scenes during sunny day in Wageningen
- Cultivar: Viper (Red)
- 6 wavelengths per pixel
9 Objects occur in a scene

<table>
<thead>
<tr>
<th>Object type</th>
<th>Classified for motion planning as</th>
</tr>
</thead>
<tbody>
<tr>
<td>Objects with distance &gt;1 m</td>
<td>Background</td>
</tr>
<tr>
<td>Unknown</td>
<td>Background</td>
</tr>
<tr>
<td>Supporting wire</td>
<td>Hard obstacle</td>
</tr>
<tr>
<td>Stick, dripper and pot</td>
<td>Hard obstacle</td>
</tr>
<tr>
<td>Construction elements</td>
<td>Hard obstacle</td>
</tr>
<tr>
<td>Stem</td>
<td>Hard obstacle</td>
</tr>
<tr>
<td>Petiole</td>
<td>Soft obstacle</td>
</tr>
<tr>
<td>Top of a leaf</td>
<td>Soft obstacle</td>
</tr>
<tr>
<td>Bottom of a leaf</td>
<td>Soft obstacle</td>
</tr>
<tr>
<td>Fruit</td>
<td>Target (ripe) or hard obstacle (unripe)</td>
</tr>
</tbody>
</table>
2.3 Background segmentation

Useful property: Solar irradiance drops at 925-975 nm
2.4 Segmentation of overexposed regions

Blue $\rightarrow$ hard obstacle, if area $\Rightarrow$ 300 pixels
Red $\rightarrow$ background, if area $<$ 300 pixels
### 3.1 Performance measure

#### Table 2
Confusion matrix.

<table>
<thead>
<tr>
<th>Classified class</th>
<th>Actual class</th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Object I</td>
<td>$TP_I$</td>
<td>$FP_I$</td>
</tr>
<tr>
<td></td>
<td>Object II</td>
<td>$FP_{II}$</td>
<td>$TP_{II}$</td>
</tr>
</tbody>
</table>

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

\[
TPR2(II) = \frac{100 \cdot TP_{II}}{TP_{II} + FP_I} \quad (\%)
\]
3.1 Performance measures

- Balanced accuracy (for one scene)

$$\text{Acc}^{2}_{\text{Bal}} = 0.5 \cdot (TPR2(I) + TPR2(II)) \quad (\%)$$

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

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

- $\text{Rob}_{Mit}$ is ‘weighting factor’ for robustness vs. accuracy
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

<table>
<thead>
<tr>
<th>Performance measure used</th>
<th>Balanced accuracy: $\text{Acc}_2^{\text{Bal}}$</th>
<th>Robust-and-balanced accuracy: $P_{\text{Rob}}$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Features (NDI spectral) in the pruned decision tree; ordered on occurrence.</td>
<td>562&amp;900; 692&amp;716; 692&amp;900; 562&amp;716; 624&amp;692; 562&amp;624</td>
<td>447&amp;624; 624&amp;900; 692&amp;716; 562&amp;624</td>
</tr>
<tr>
<td>Balanced accuracy $\text{Acc}_2^{\text{Bal}}$ (%)</td>
<td>77.1</td>
<td>75.4</td>
</tr>
<tr>
<td>$M_{\text{TPR}<em>2(\text{hard})}(SD</em>{\text{TPR}_2(\text{hard})})$ (%)</td>
<td>66.5 (17.2)</td>
<td>59.2 (7.1)</td>
</tr>
<tr>
<td>$M_{\text{TPR}<em>2(\text{soft})}(SD</em>{\text{TPR}_2(\text{soft})})$ (%)</td>
<td>87.4 (7.0)</td>
<td>91.5 (4.0)</td>
</tr>
</tbody>
</table>

- Reduction of 2%
- Reduction of ± 50%
Separability for 15 binary combinations of plant parts.
5.5 Approach to classify 5 plant parts

Stem, TL, BL, Fruit and Petiole

A1

Stem and Fruit

A2

Fruit (hard)

A3

TL, BL and Petiole

BL and Petiole

A4

BL (soft)

Petiole (soft)
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

Detection rate per class [%]

Classified as: Stem TL BL Fruit Pet

GT Stem GT TL GT BL GT Fruit GT Pet
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!!!