Crop/Weed Discrimination for Autonomous Weeding Robots

Dr Grzegorz Cielniak

Lincoln Centre for Autonomous Systems
University of Lincoln

1st Online Conference on Agri-Food Robotics, March 2020

Challenges

Natural variation in crops/weeds

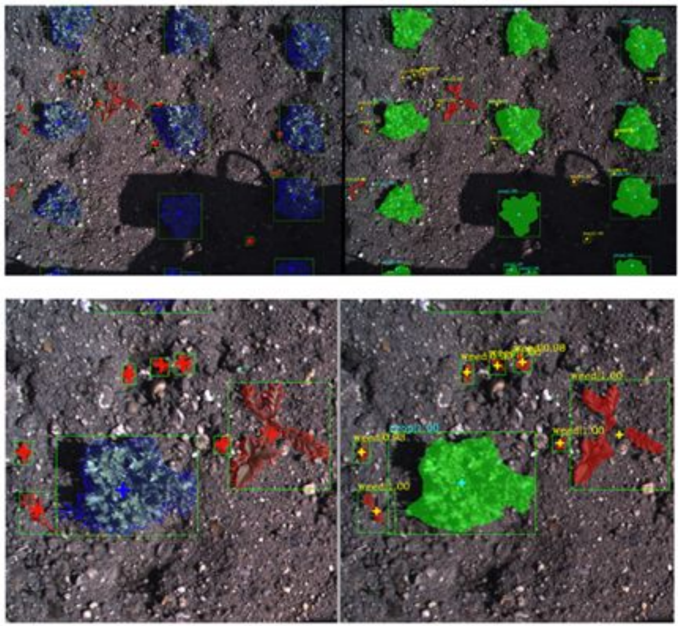
Changes due to plant growth

Changing weather and lighting conditions: challenge for current sensing technology

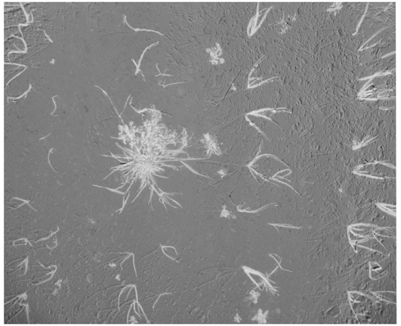
Irregular arrangements of crop beds

Data-driven techniques need loads of data: not there yet

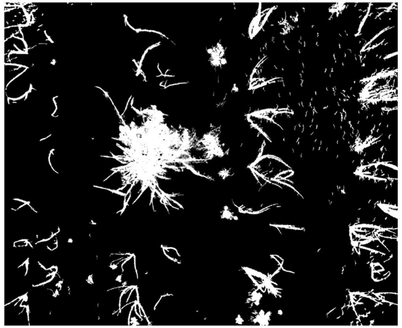
Generalisation between crops and fields



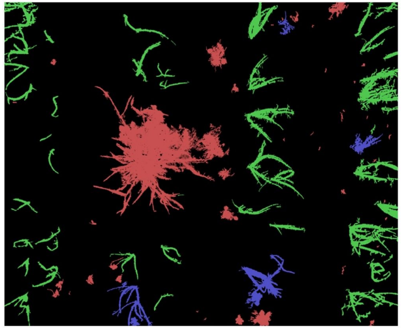
Segment Vegetation then Discriminate

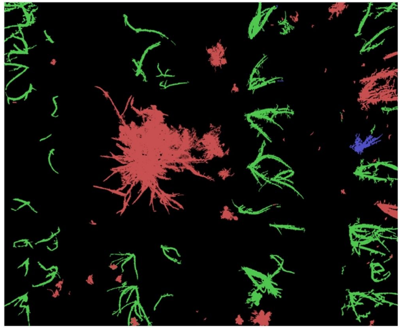


(a)



(b)

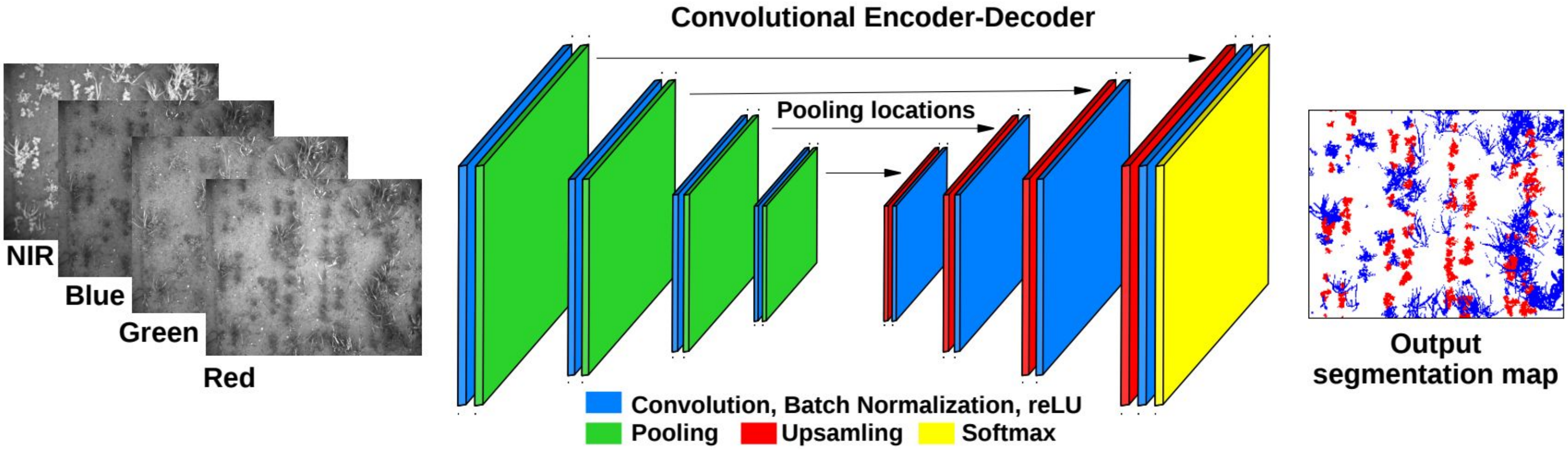




Method	Otsu	RATS	max-tree
Dataset		*Onions 2017*	
Precision	74.41%	47.78%	**75.36%**
Recall	80.25%	**87.54%**	83.32%
F_1	77.22%	61.82%	**79.14%**
Parameters	–	$\eta = 8$	$\Delta = 30$
Dataset		*LowVeg*	
Precision	0.40%	0.44%	**75.66%**
Recall	**96.33%**	95.77%	64.96%
F_1	0.80%	0.88%	**69.90%**
Parameters	–	range	$\Delta = 25$
Dataset		*Sugar Beets 2016*	
Precision	59.93%	50.52%	**76.21%**
Recall	96.81%	**98.64%**	93.87%
F_1	74.03%	66.82%	**84.13%**
Parameters	–	$\eta = 14$	$\Delta = 45$

Descriptor (len)	**positional information**					
	Crop		**Weed**		κ	**Acc[%]**
	p[%]	**r[%]**	**p[%]**	**r[%]**		
			Sugar Beets 2016			
position (1)	85.79	94.14	83.92	66.23	0.64	85.32
HOG (200)	85.02	94.91	84.81	62.97	0.62	84.98
LBP (18)	89.56	94.58	86.30	75.58	0.73	88.67
AP:A+I+S (9)	91.93	94.30	86.92	82.08	**0.78**	**90.44**
			Carrots 2017			
position (1)	47.90	21.47	67.23	**87.33**	0.10	64.18
HOG (200)	45.28	40.75	68.88	72.70	0.14	61.31
LBP (18)	53.51	52.97	74.08	74.49	0.28	66.82
AP:A+I+S (8)	57.70	54.48	76.04	78.35	**0.33**	69.96

CNN-based Classification

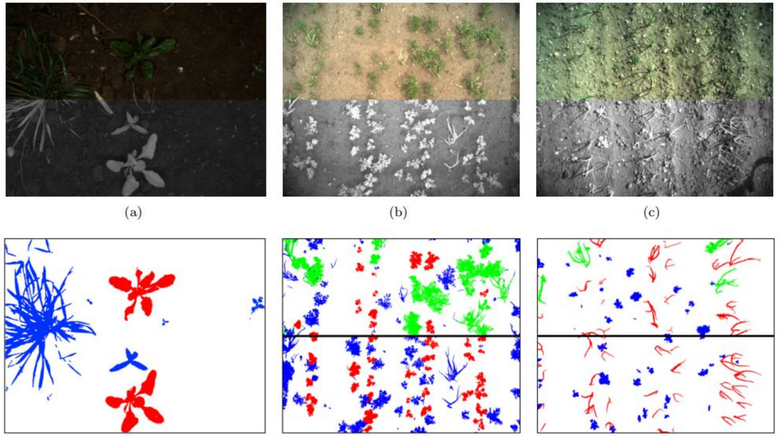


Crop to Crop Transfer

Tested on 3 crops: sugar beet, carrots and onions

Possible, only minor hit on the performance

Reduces training time by 80%

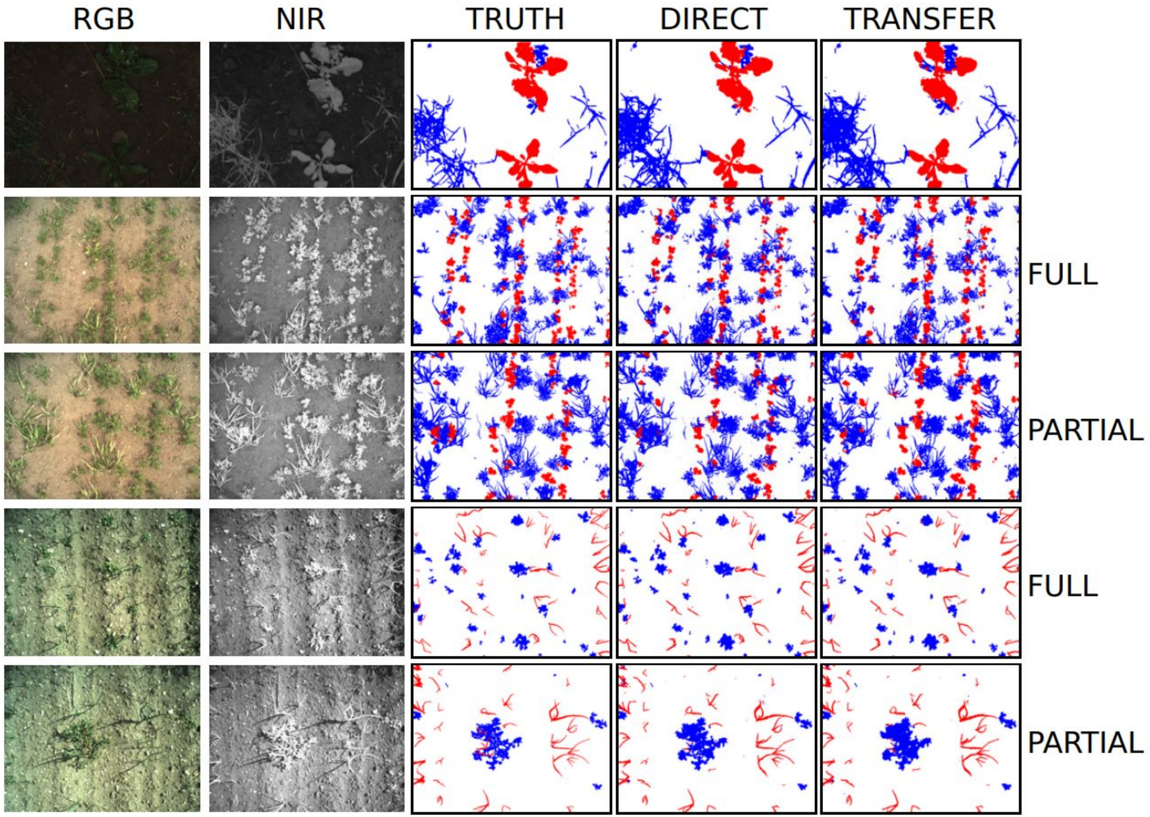


Data			iter.	Pixel-based						
train	weights	test	(× 1000)	Soil p	Soil r	Weed p	Weed r	Crop p	Crop r	κ
Train on crop X, test on crop X, with fully labelled data										
SB16	–	SB16	45	99.91	98.99	66.05	94.48	94.71	97.46	91.24
CA17-f	–	CA17-f	28	98.16	96.38	80.63	87.02	75.97	77.68	83.24
ON17-f	–	ON17-f	39	99.62	98.72	83.76	92.79	72.28	86.64	84.88
Train on crop X, retrain and test on crop Y, with fully labelled data										
SB16	CA17-f	SB16	9.7	99.94	98.58	59.67	95.58	92.29	97.31	88.74
SB16	ON17-f	SB16	7.4	99.93	98.28	52.92	96.24	92.33	95.60	86.42
CA17-f	SB16	CA17-f	5.5	97.81	96.58	81.97	85.12	75.29	79.56	83.05
CA17-f	ON17-f	CA17-f	5.9	98.15	96.26	81.03	86.51	74.27	79.07	83.05
ON17-f	SB16	ON17-f	9.0	99.62	98.65	82.44	92.22	71.39	86.43	84.21
ON17-f	CA17-f	ON17-f	6.9	99.51	98.62	89.31	87.59	65.80	89.24	83.26

Rapid Annotations

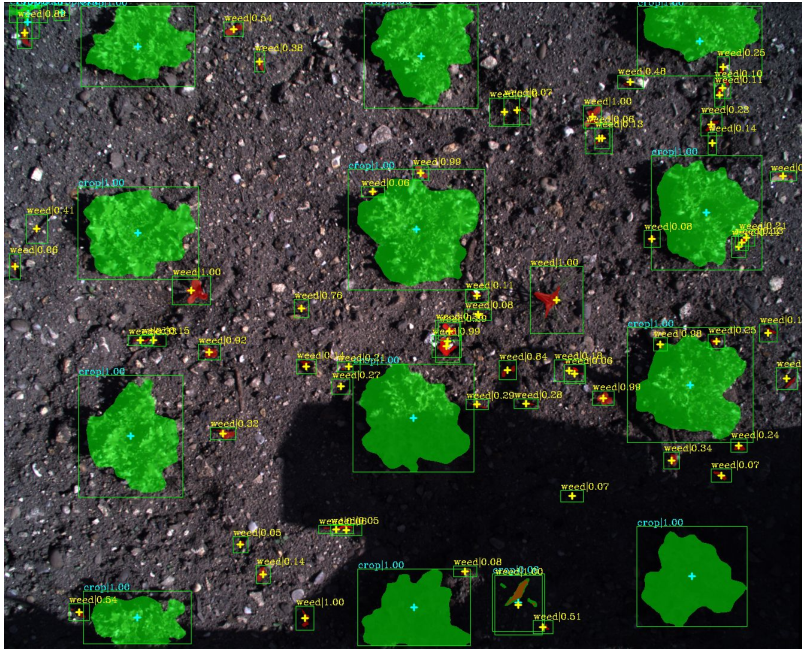
Classification performance
2% less than on full labels

Data			
train	**weights**	**test**	κ
SB16	–	SB16	91.24
CA17-f	–	CA17-f	83.24
ON17-f	–	ON17-f	84.88
with fully labelled data			
SB16	CA17-f	SB16	88.74
SB16	ON17-f	SB16	86.42
CA17-f	SB16	CA17-f	83.05
CA17-f	ON17-f	CA17-f	83.05
ON17-f	SB16	ON17-f	84.21
ON17-f	CA17-f	ON17-f	83.26
partially labelled data for retraining			
CA17-p	SB16	CA17-f	79.37
CA17-p	ON17-f	CA17-f	79.04
ON17-p	SB16	ON17-f	83.52
ON17-p	CA17-f	ON17-f	82.66



Current/Future Work

- Transfer learning
- Reducing annotation effort
- Semi-automated clustering-based learning with minimal feedback from the user
- Exploiting the spatial structure of rows (when available)
- Locating stems of plants
- Temporal models for prediction of appearance



References

People

- Dr Petra Bosilj, Dr Michael Stout, Prof. Tom Duckett and Dr Grzegorz Cielniak

Publications

- Bosilj et al. 2019, *Transfer learning between crop types for semantic segmentation of crops versus weeds in precision agriculture.* Journal of Field Robotics
- Bosilj et al. 2018, *Analysis of morphology-based features for classification of crop and weeds in precision agriculture.* IEEE Robotics and Automation Letters
- Bosilj et al. 2018, *Connected attribute morphology for unified vegetation segmentation and classification in precision agriculture.* Computers in Industry

Projects

- Development and field testing of the next generation of vision-guided weeding systems, IUK 2019
- Integration of the Vision-based Weed Identification System into Robotic Weeders, BBSRC 2017
- 3D Vision-based Crop-Weed Discrimination for Automated Weeding Operations, IUK/BBSRC 2016