Fruit detection in 3D and shape estimation for long term autonomous robotic harvesting

Justin Le Louedec, University of Lincoln

Supervised by :

- Grzegorz Cielniak, University of Lincoln
- Charles Whitfield, NIAB EMR





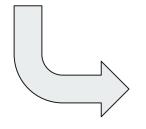
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Contributions of the PhD

- Detection of strawberries in 3D:
 - Effective data acquisition
 - Offering conclusions and study of the usability of 3D information and sensing technologies for strawberry harvesting
- Shape information analysis for biologist and growers (phenotyping and yield analysis):
 - Reconstruction from partial view -> Only one side view of the plant
 - Inferring shape and size from 3D scans
 - More biologically oriented shape analysis

Challenges as of today

- 3D information is more difficult and complex than images to process:
 - Higher dimension and more complex information
- Understanding and completing shape requires an understanding of the environment



3D information add a lot more information concerning shape, size, localisation, occlusions and spatial relationship between objects and harvester

Detection in 3D

Detection in 3D : VISAPP 2020

INU INSIDE

Intel Realsense

Pico Zense, ToF

Camera

D435i

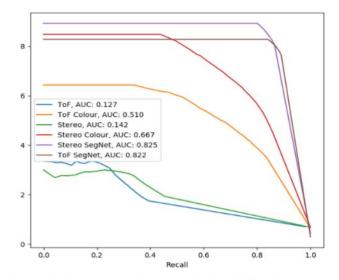


Figure 3: Precision-recall curves for the different networks indicating also area under the curve (AUC).

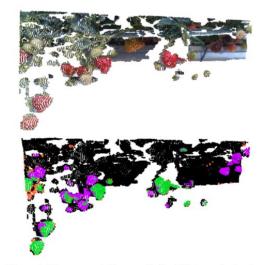
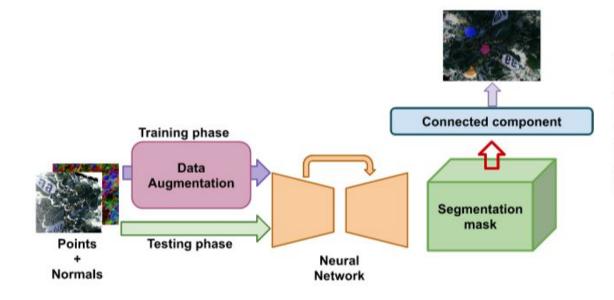


Figure 4: The segmentation results for *PNet_{colour}* trained on data from the stereo camera: the original point cloud (top), segmentation results (bottom). The colours indicate: TP in green, FP in orange, FN in purple and TN in black.

Detection in 3D : CVPR Workshop 2020



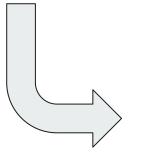
	FEC	NN	FEC	NN	FEC	NN
Trained Tested	Spain		UKI		UK2	
Spain	0.65	0.87	0.56	0.79	0.61	0.81
UK1	0.94	0.76	0.96	0.95	0.92	0.93
UK2	0.93	0.76	0.92	0.91	0.92	0.93
Mean	0.84	0.80	0.81	0.88	0.82	0.89

Table Comparison of the MaP for the instance detection masks. We compare FEC and the neural network, with the dataset used for training at the top, and the one used for testing on the left side. We also show the average performances for each training set.

Understanding shape information

Shape information

- Shape encapsulate a lot of information about the fruits and plant quality
- Partial view of the objects (seen from one side) creates unseen and information to infer
- Goals of creating compact and useful descriptors and reconstruct shape from partial view



Understanding shape to provide information to agronomist, biologist and growers about berries and fruits size, shape and aspect to improve yield and production

Shape estimation : UKRAS 2020

TABLE I

The volume and surface area estimation results from the reconstruction process of 15 3D models of strawberries (Note the objects were scaled during capture process).

	Original	Reconstructed	Deviation
Volume $(\mu \pm \sigma) \ cm^3$	45 ± 46	45 ± 46	$\sim 1\%$
Surface area $(\mu \pm \sigma) \ cm^2$	280 ± 160	277 ± 160	$\sim 1\%$

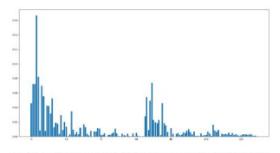
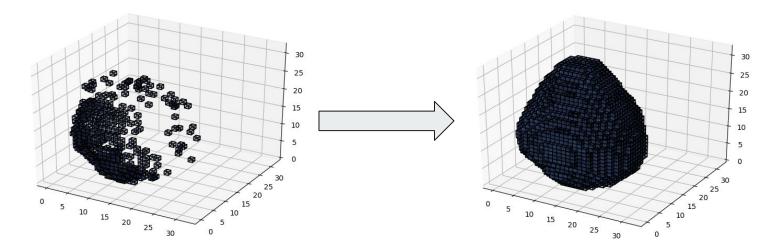


Fig. 2. Spherical harmonics coefficients responsible for main shape information

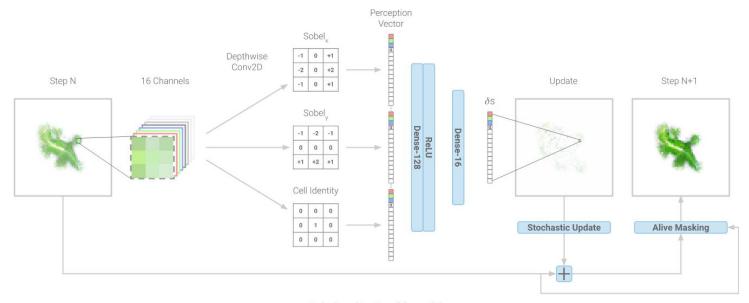
Fig. 1. Example of strawberry point clouds (left example for each pair) and their reconstructions(right example for each pair), for two particular shapes.

Compact way of encapsulating entire shape information to report on it to biologist and growers



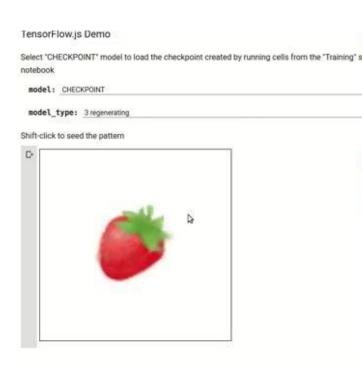
Encoding shape using voxels and using cellular automata for regeneration, recreating shape from partial one

Cellular automata for regeneration

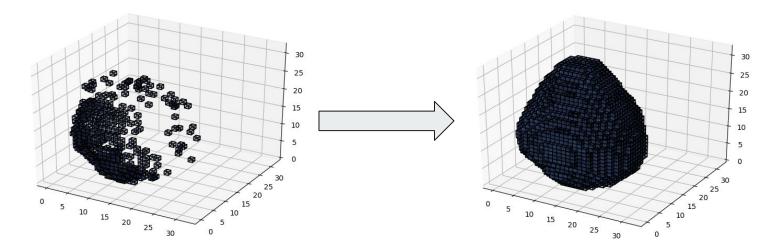


A single update step of the model.

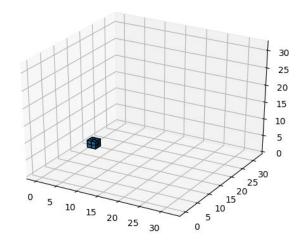
Growing Neural Cellular Automata, Mordvintsev et al.







Encoding shape using voxels and using cellular automata for regeneration, recreating shape from partial one



Conclusion

- Strong study of using 3D information for detections and localisation
- Preliminary work on shape estimation, more to come
- 3D information is difficult to process and manage, but could bring a lot of advances
- Creating gap between computer graphics, computer vision and geometry is the key for shape understanding

Future work

• Human centered shape understanding : Adding understandable parameters to

reconstruction and analysis

- Bridging gap between simulation and perfect data, with real world *good* data :
 - Transfer learning

