ROBOTICS SOLUTIONS TO STRAWBERRY HARVESTING (AND LOGISTICS)

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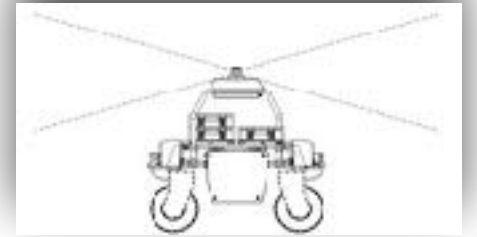
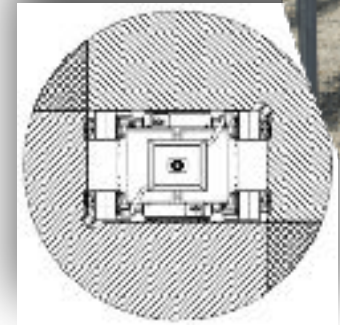
Challenges in Soft Fruit Production

Reliance of manual labour due to complex operations

Shrinking workforce due to socio-political pressures and ageing population

Thorvald - a modular mobile platform





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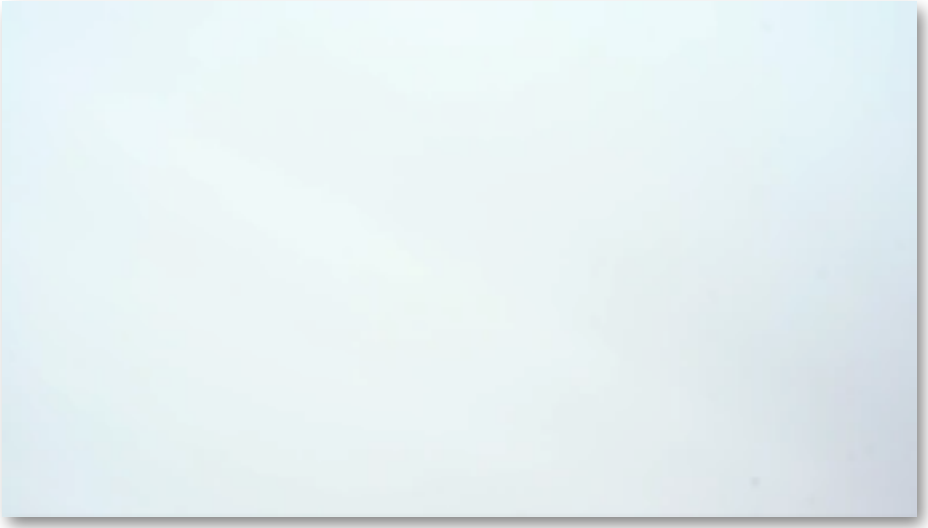
Dedicated Strawberry Production Site

Realistic environment for data collection, algorithm development and field testing



RASberry - https://rasberryproject.com/

RASberry: Robotic and Autonomous Systems for Berry Production

- **Field Logistics and Autonomy (also working with Humans)**
- **Fruit Perception (for picking, phenotypic and yield prediction)**
- **Autonomous Picking Solutions**

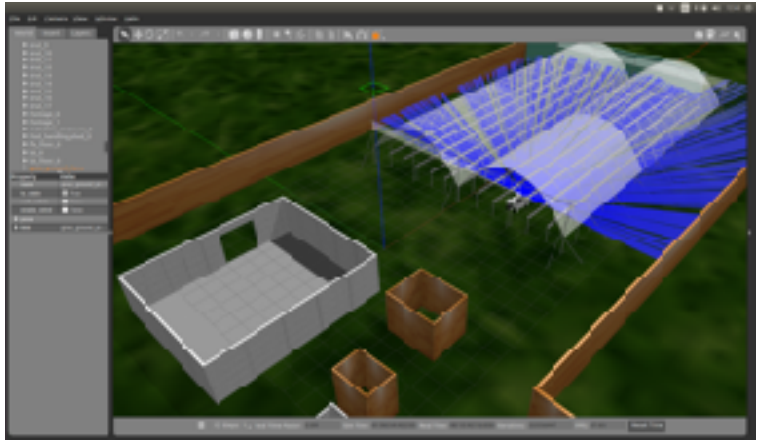
Field Logistics and Autonomy

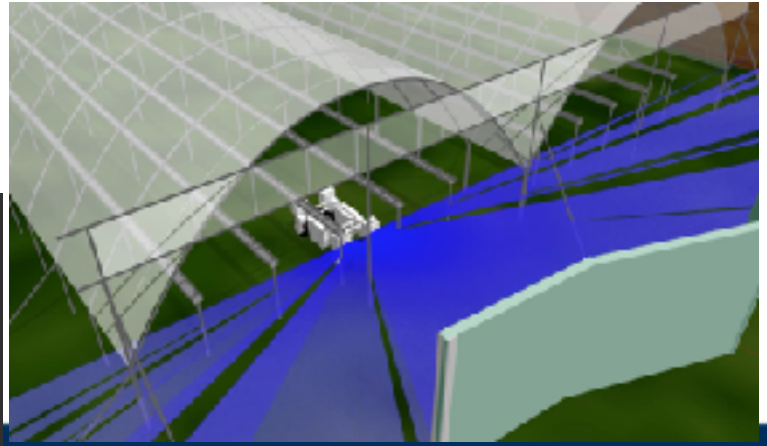
Navigation and Autonomy

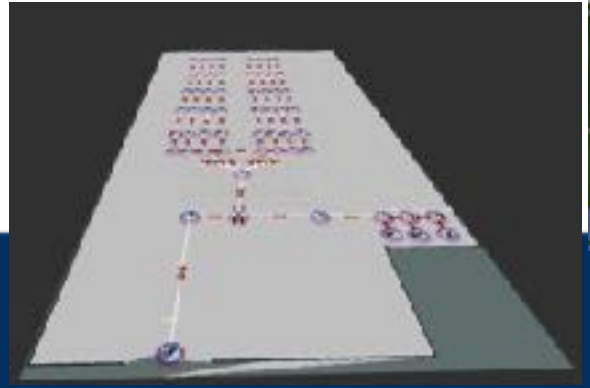
hybrid GPS & laser-based navigation

Realistic simulation environments

Automated tuning of parameters
(ICRA 2020)



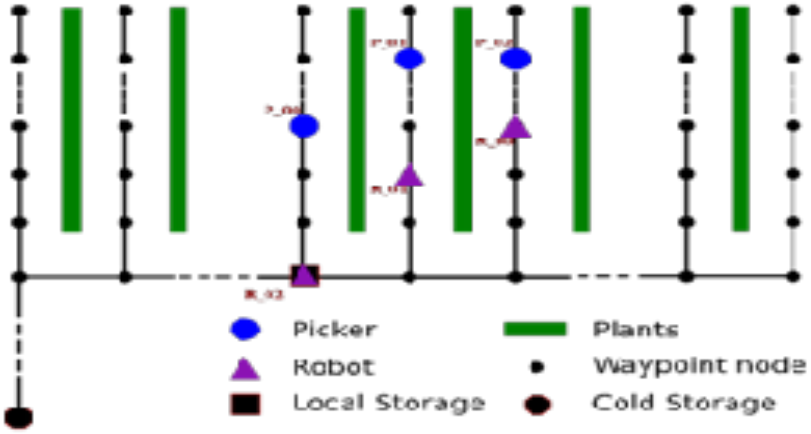




Fleet Coordination

Avoiding deadlocks and moving robots in the field efficiently.

- Discrete Event Simulator (DES)
- Picker and robot agents with discrete states and transitions
- Navigation environment is discretised
- Really fast simulations compared to continuous-time simulations



RASberry DES Visualisation

Das, G. P. and Cielniak, G. and From, P. J. and Hanheide, M. (2018). *Discrete Event Simulations for Scalability Analysis of Robotic In-Field*

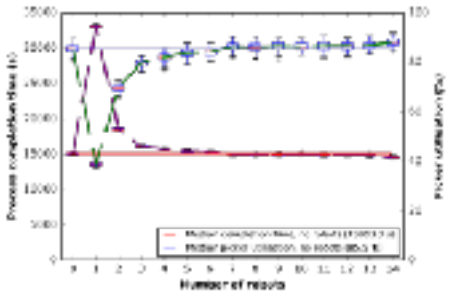
Fleet Coordination

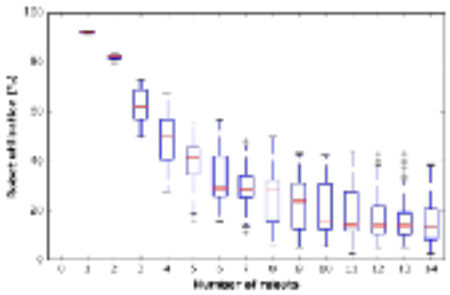
Normal Operation

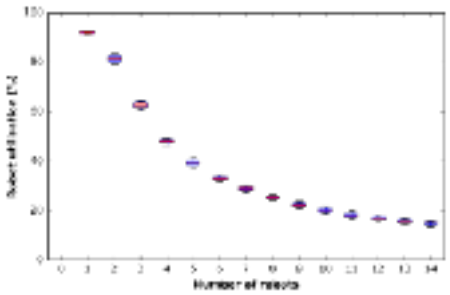
- A picker uses "Call-A-Robot" to request for a robot
- The coordinator adds the call to a task queue
- During processing of the task,
  - The coordinator assigns an idle robot to the picker
  - The robot goes to the picker and collect full trays
  - The picker can set "tray loaded" using "Call-A-Robot"
  - The robot goes to storage and trays are unloaded
  - The robot returns to its base station

Fleet Coordination - DES

- Anticipatory scheduling (predicting when the robot might be needed)
- Analysis of scalability in real-world environments (#pickers vs. #robots)
- Useful for global trajectory planning for individual robots







Perception of Humans

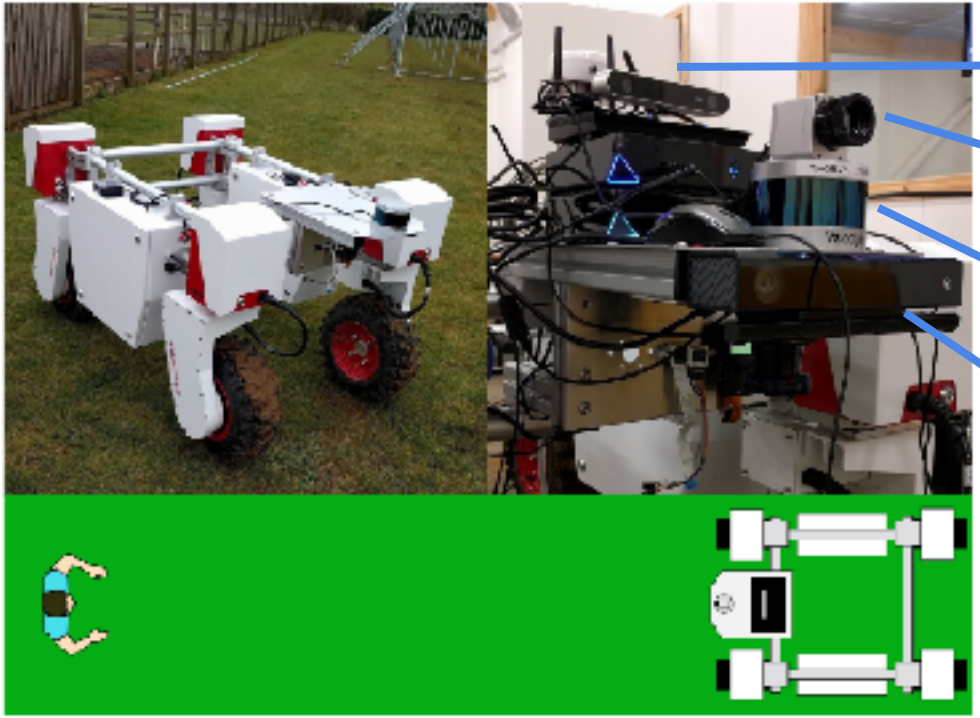
Motivations:

- Safety during navigation
- Approach or avoid workers in the field

Challenges:

- Sensor noise, dirt
- Occlusions, lighting, misclassification
- Wide open areas, uneven terrain

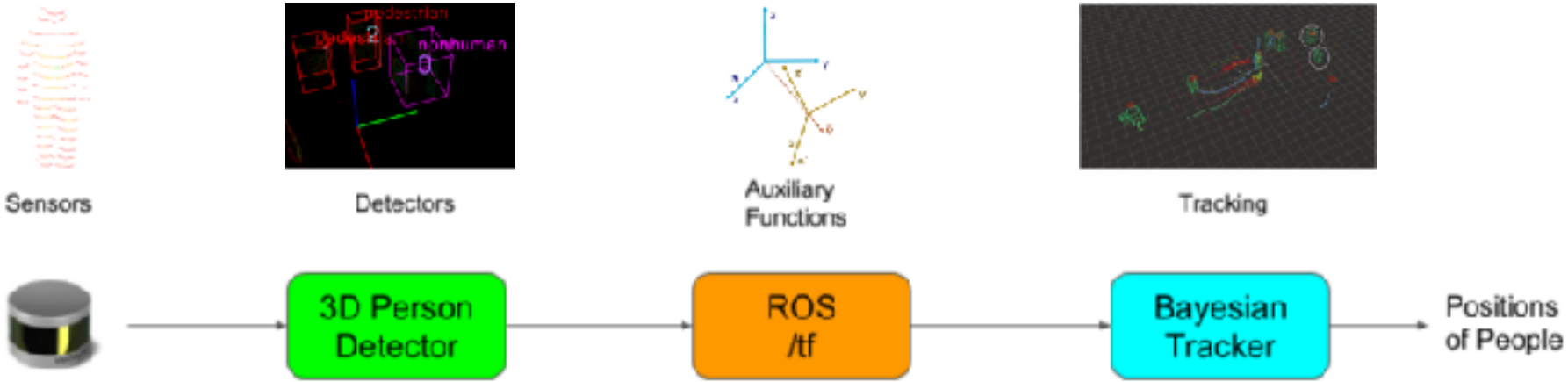
Sensors



- Stereo camera
- Thermal camera
- 3D LiDAR
- RGB-D camera

Human Detection and Tracking

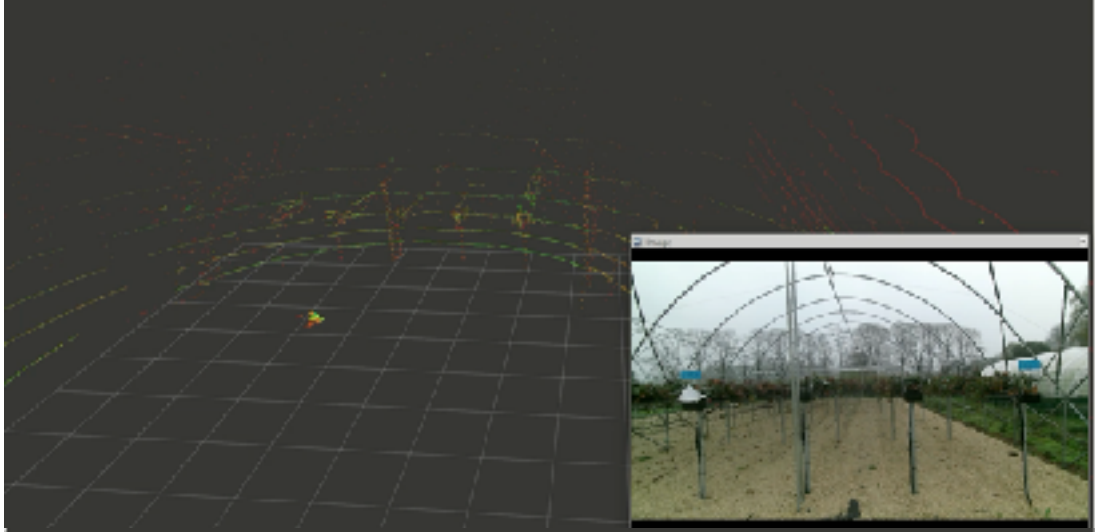
- Independent sw modules for **human detection** are assigned to each sensor
- Detections are transformed from (local) sensor to (global) robot frame of ref.
- Finally combined in a multisensor/multiperson Bayesian estimator (i.e. UKF)

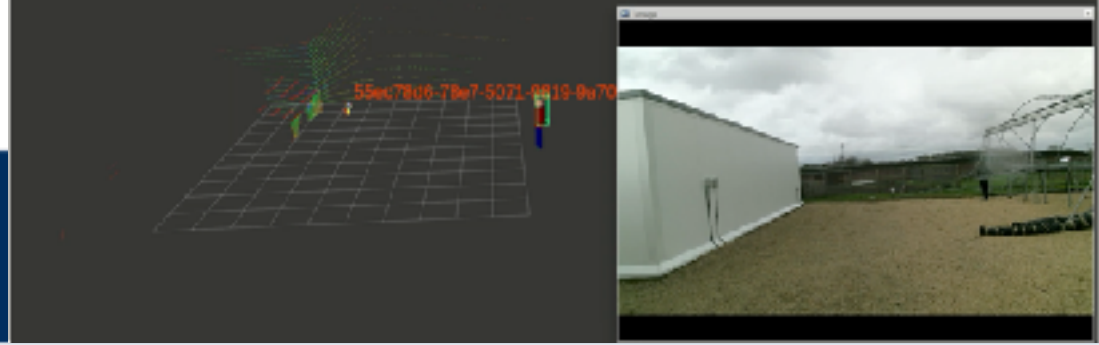


Examples in the Field

Single person

Multiple people





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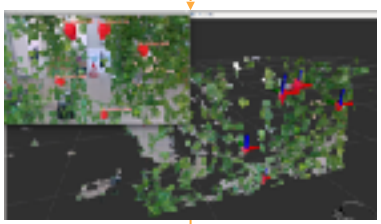
Fruit Perception and Tracking

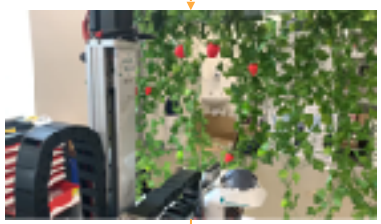
Robotic Perception for the Soft Fruit Industry

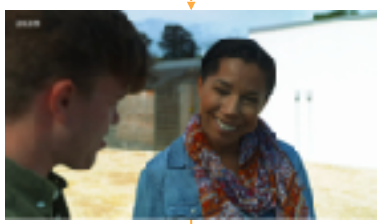
Research Question

Where are the berries?	Where are the berries in real world coordinates?	How can we harvest the berries?	Can we harvest berries we can't see?	Have I seen this berry before?

Solution







Industry/Grower Impact

Detecting Berries From Images. Enables Analysis.	Enables Harvesting Applications and Virtual Agronomy.	Reduces labor demand, damage to berries, increases harvest throughput.	Improves detection and harvesting rates.	Fruit count information, maturity maps, and yield estimation.

Technical Challenges

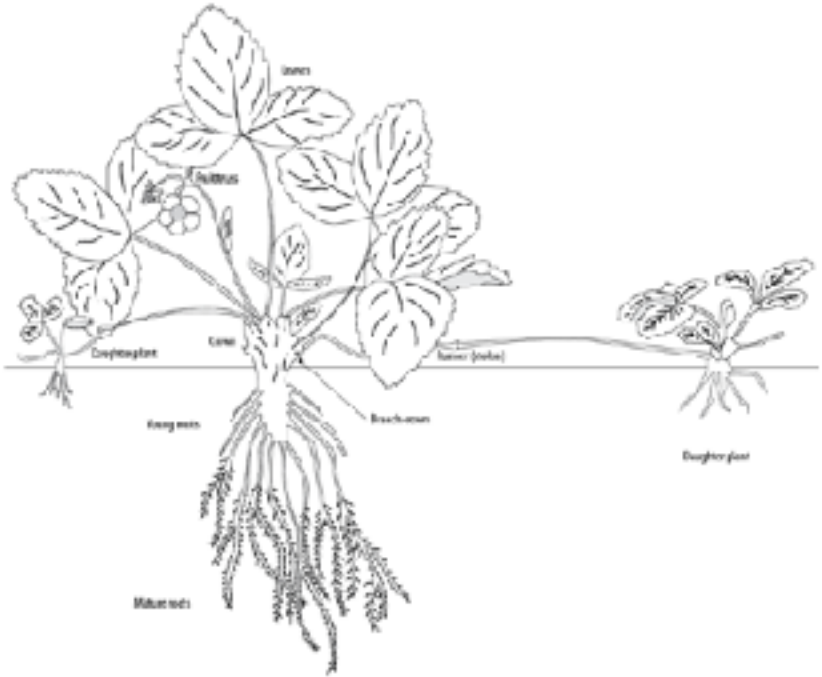
Outdoors - changing lighting/weather conditions

Natural variation of fruit/plants in appearance, shape, orientation

Temporal changes and metamorphosis due to growth

Occlusions by other berries, leaves, trellis

Limitations of the current sensing technology



L*a*b*Fruits

Problem

Environmental features outdoors (sunlight intensity, weather conditions, etc.) affect perceptual appearance of objects and consequently the performance of detection systems.

Solution

We fuse RGB data with bio-inspired features to classify produce over a greater number of conditions.

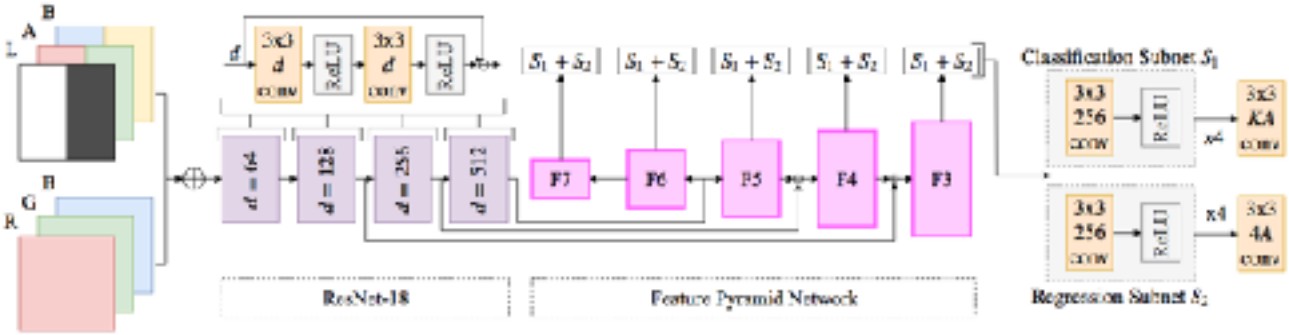
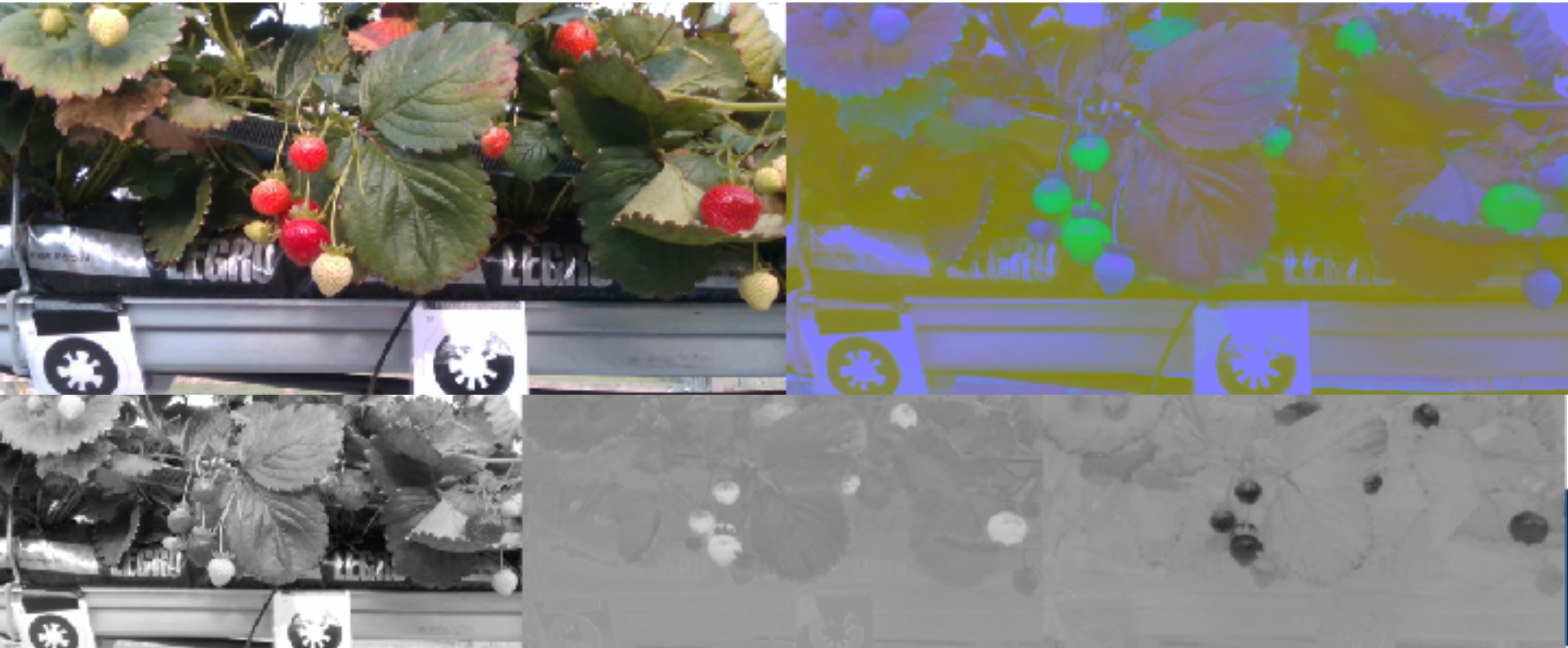


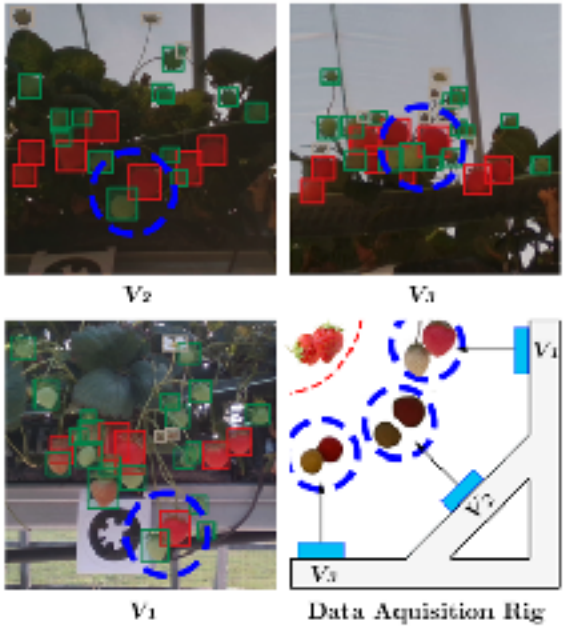
Figure L*a*b*Fruits: Human-inspired deep learning architecture.

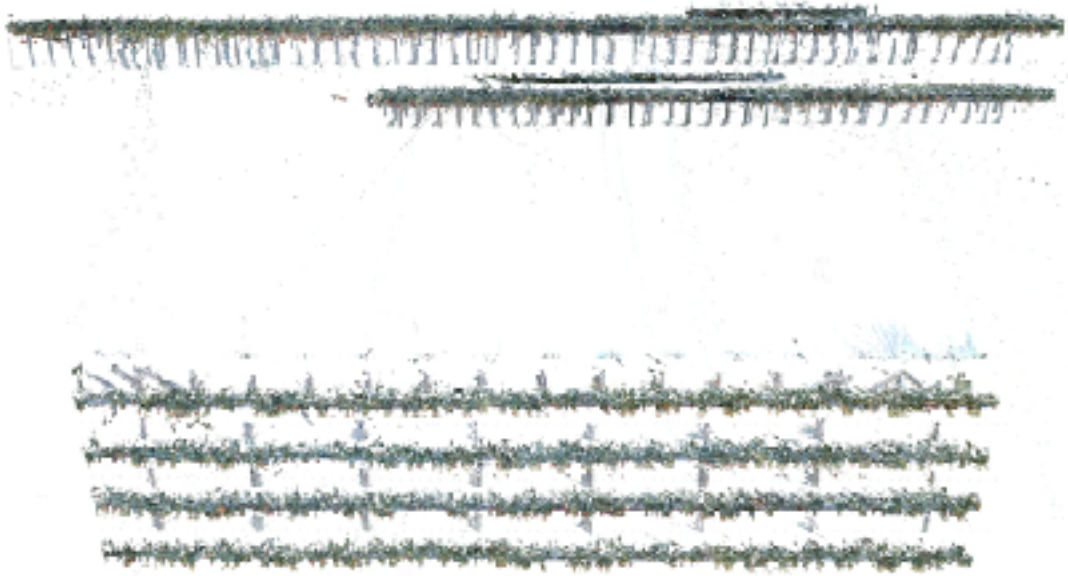
Human-Inspired Features

Colour Opponency



Data Collection (summer 2019)





Viewpoint	Training	Validation	Total
V_1	120 (80%)	10 (6.6%)	130
V_2	0 (0%)	10 (6.6%)	10
V_3	0 (0%)	10 (6.6%)	10
Total	120 (80%)	30 (20%)	150

Bounding Boxes	Ripe	Unripe	Total
Training	673	2680	3353
Validation	217	649	886
Total	890	3329	4219

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Fruit Detection

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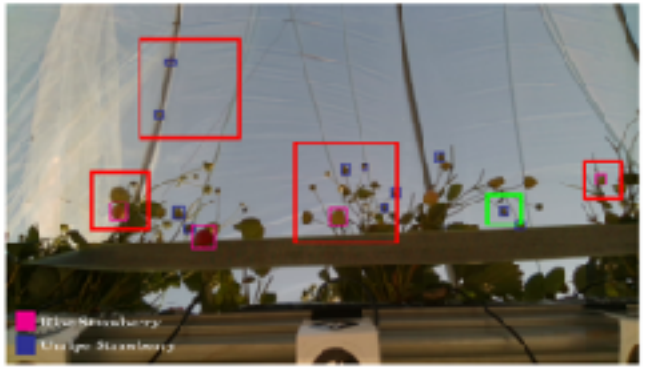
Results

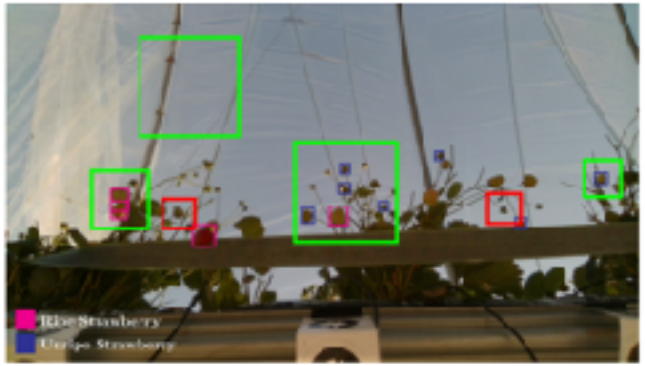
Class	View	Score	RGB	CIE Lab	Early Fusion
Both Classes	V_1	F_1	0.744	0.710	**0.747**
Both Classes	V_1	AP	0.722	0.695	**0.748**
Both Classes	V_1	AR	0.870	0.844	**0.909**
Both Classes	V_{2-3}	F_1	0.680	0.622	**0.704**
Both Classes	V_{2-3}	AP	0.659	0.586	**0.694**
Both Classes	V_{2-3}	AR	0.812	0.761	**0.851**
Ripe Strawberry	V_1	F_1	0.683	0.625	**0.697**
Ripe Strawberry	V_1	AP	0.616	0.571	**0.678**
Ripe Strawberry	V_1	AR	0.807	0.767	**0.892**
Ripe Strawberry	V_{2-3}	F_1	0.697	0.662	**0.729**
Ripe Strawberry	V_{2-3}	AP	0.659	0.621	**0.719**
Ripe Strawberry	V_{2-3}	AR	0.806	0.777	**0.877**
Unripe Strawberry	V_1	F_1	**0.805**	0.795	0.797
Unripe Strawberry	V_1	AP	**0.828**	0.819	0.818
Unripe Strawberry	V_1	AR	**0.933**	0.922	0.927
Unripe Strawberry	V_{2-3}	F_1	0.663	0.582	**0.679**
Unripe Strawberry	V_{2-3}	AP	0.658	0.552	**0.668**
Unripe Strawberry	V_{2-3}	AR	0.819	0.745	**0.825**

Table 7. Performance of the Early Fusion Network on a Nvidia GTX 1080 Ti 11GB (single forward pass).

Resolution	Model Inference Time	Frames Per Second
1920 × 1080	0.073 s	13.71
1280 × 736	0.038 s	26.33



(a) RGB network detection showing failure cases.



(b) Early Fusion network detection showing improved results.

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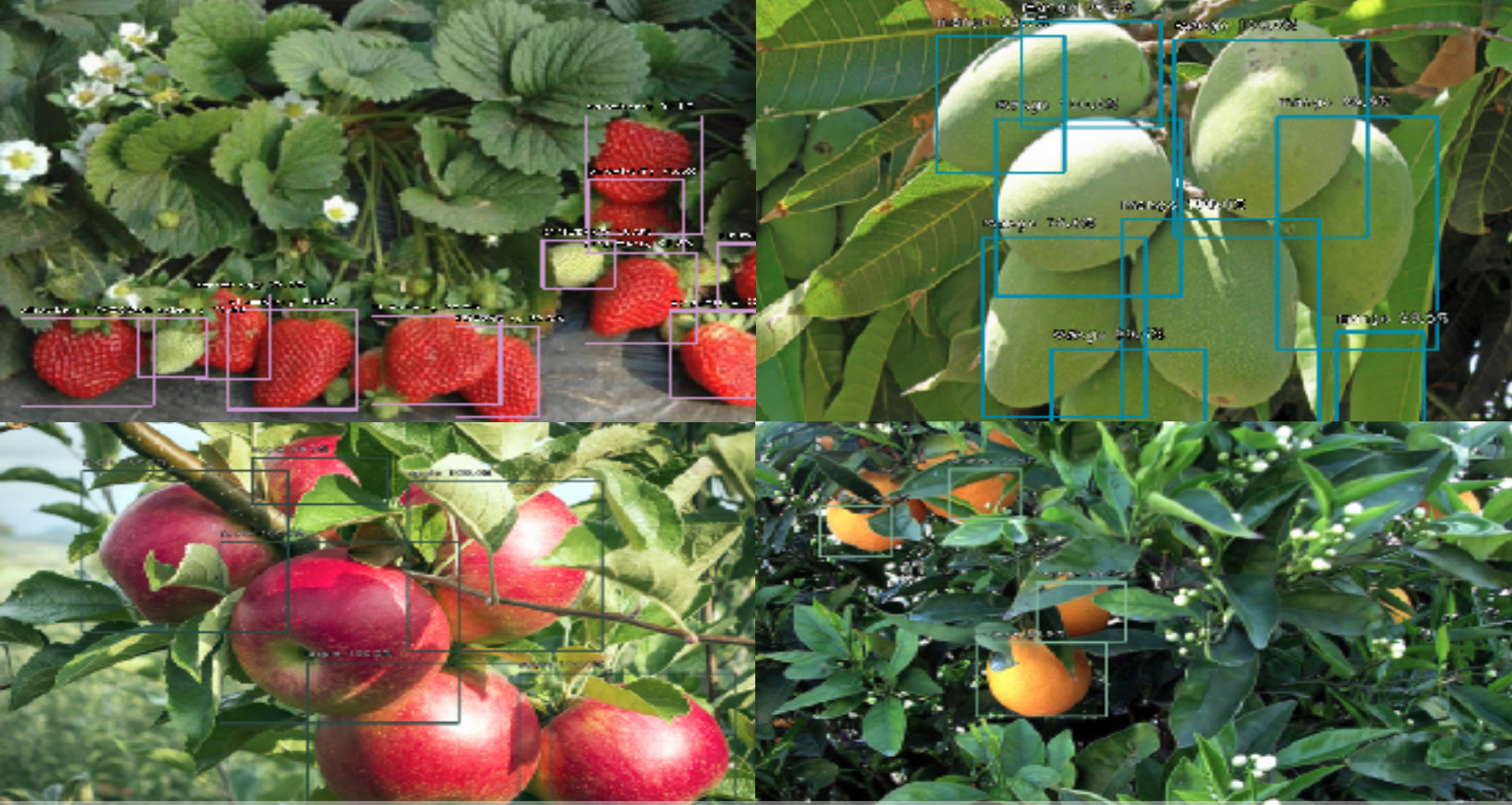


Not just for strawberries!

SOTA in DL for Fruit Detection

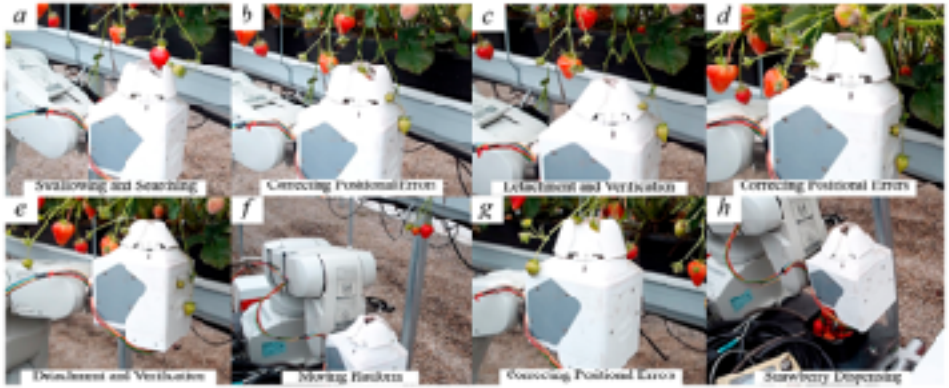
Method	# Images	Availability	Viewpoint	Multi Spectra	Controlled	Natural
Yu et al. [34]	1900	✗	Side on (Close)	✗	✓	✗
Chen et al. [35]	12526	✗	Aerial	✗	✗	✓
Lamb and Chuah [36]	4550	✗	Ground	✗	✗	✓
Ge et al. [37]	-	✗	Side on	✗	✗	✓
Sa et al. [8]	122	✓	Side on	✓	✓	✗
L*a*b*Fruits (Ours)	150	✓	Multiple	✓	✗	✓

Method	Network	AP (IoU 0.5)	F_1 (IoU 0.5)	Inference Speed (s)
Yu et al. [34]	Mask R-CNN - ResNet-50	-	-	0.13 @ 640 × 480 px
Chen et al. [35]	Faster R-CNN - ResNet50	0.77	-	0.11 @ 480 × 380 px
Lamb and Chuah [36]	Single Shot Detector (SSD)	0.84	-	0.61 @ 360 × 640 px
Ge et al. [37]	Mask R-CNN - ResNet-101	0.81	0.90	0.62 @ 640 × 480 px
Sa et al. [8]	Faster RCNN - VGG-16	-	0.79	0.39 @ 1296 × 964 px
L*a*b*Fruits (Ours)	RetinaNet, ResNet-18	0.75	0.75	0.07 @ 1920 × 1080 px

Yield Prediction (Fruit Counting)

Picking

Picking



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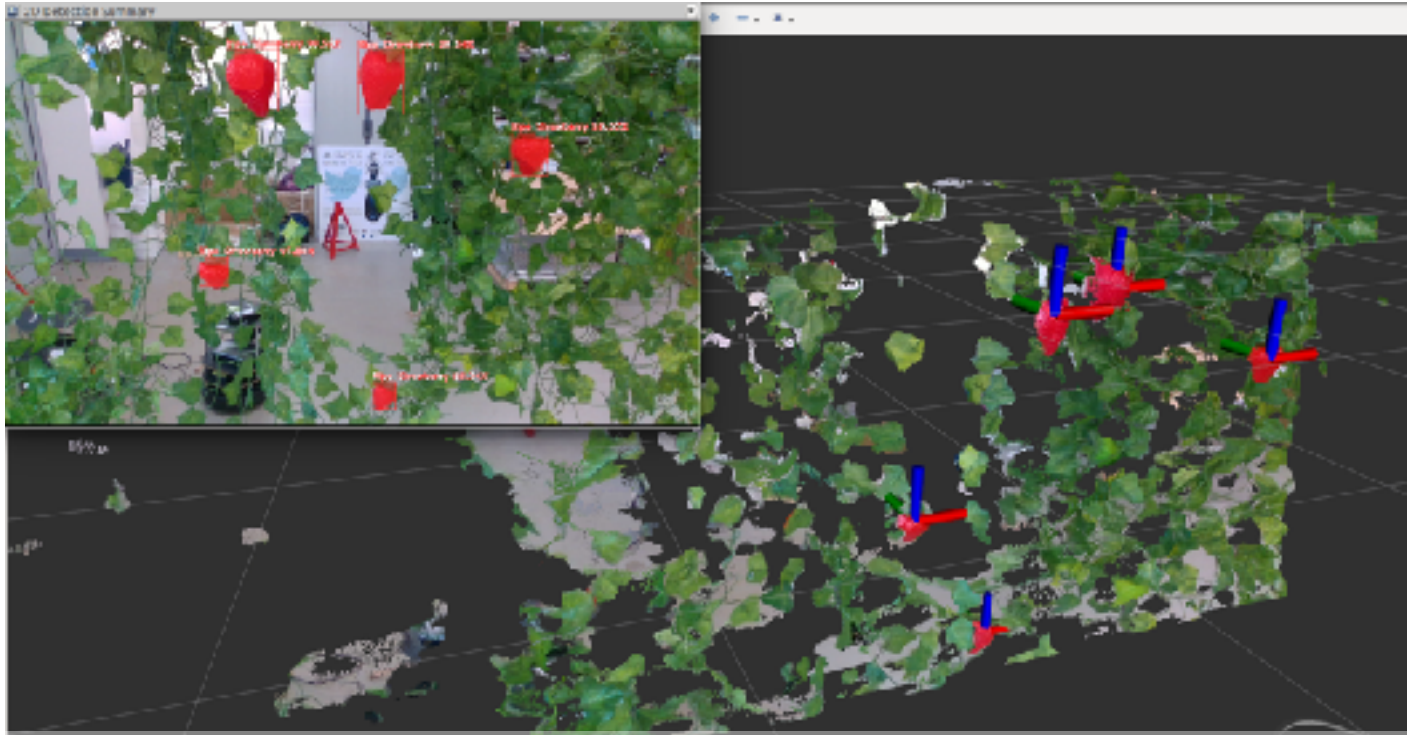
Xiong, Y.; From, P. J.; Isler, V.. Design and Evaluation of a Novel Cable-Driven Gripper with Perception Capabilities for Strawberry Picking Robots. 2018 IEEE ICRA

L-CAS

Fruit Localisation (3D projection)



3D Projection of Strawberry Detections Showing Accurate Localisation

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Harvesting Localisation Failures

Pros:

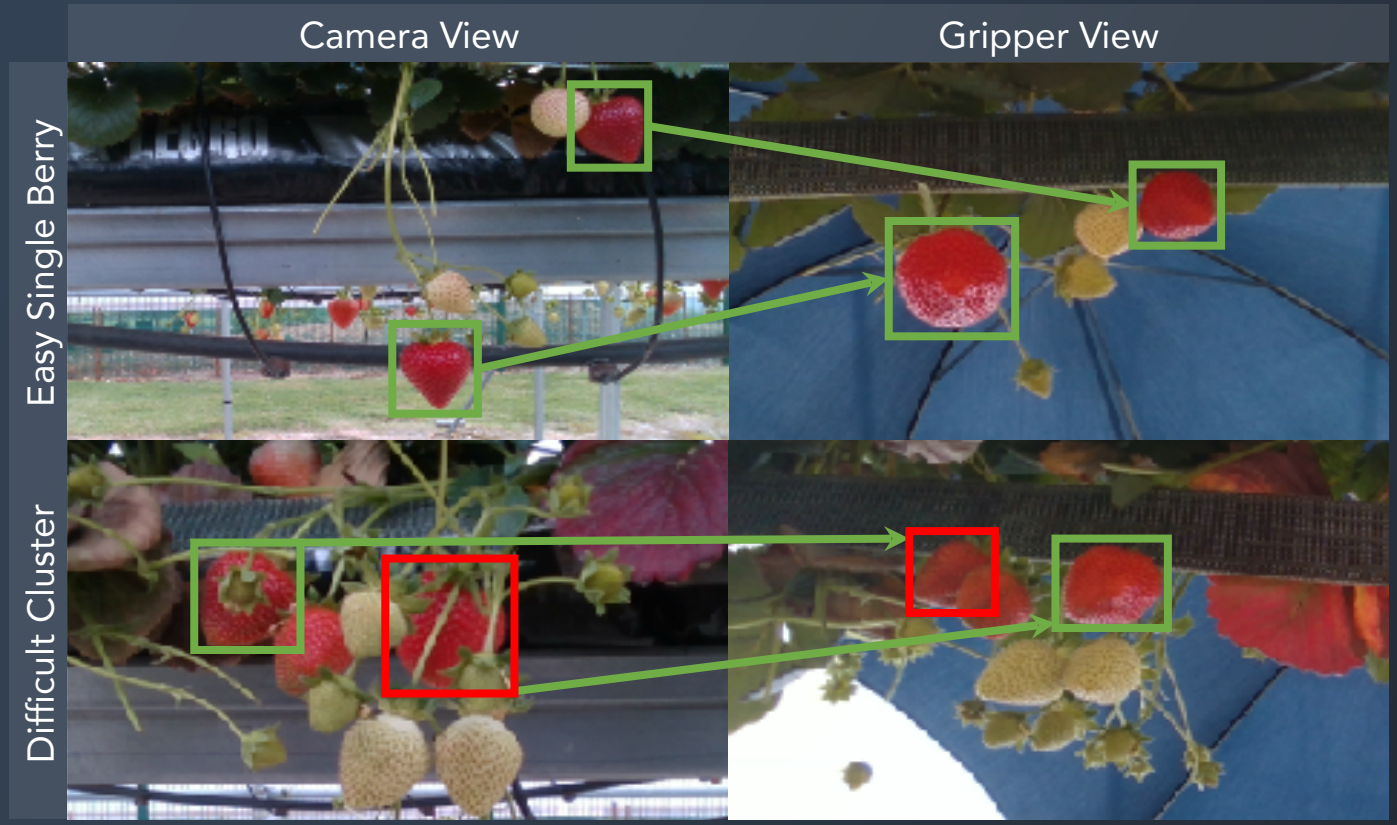
Current detection system can now successfully pick single berries with good separation.

Fast 3D detections.

Cons:

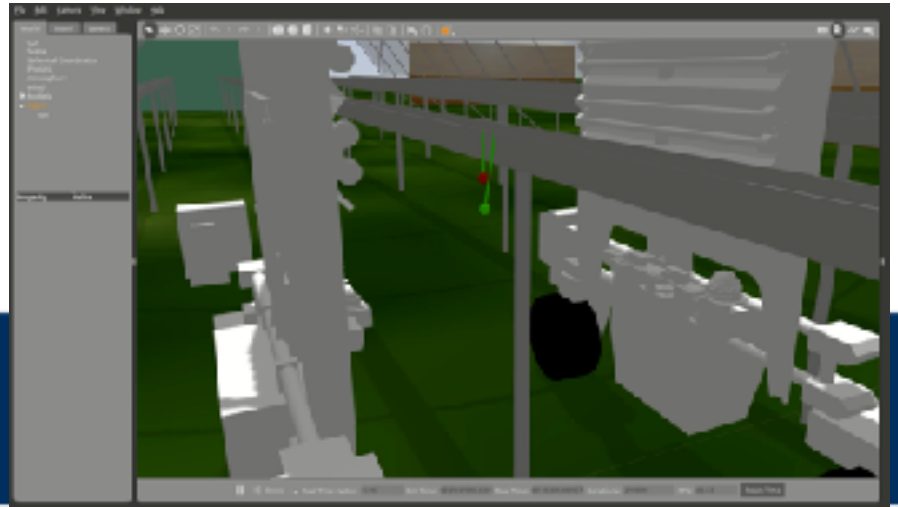
Cannot pick berries in clusters due to unforeseen obstructions.

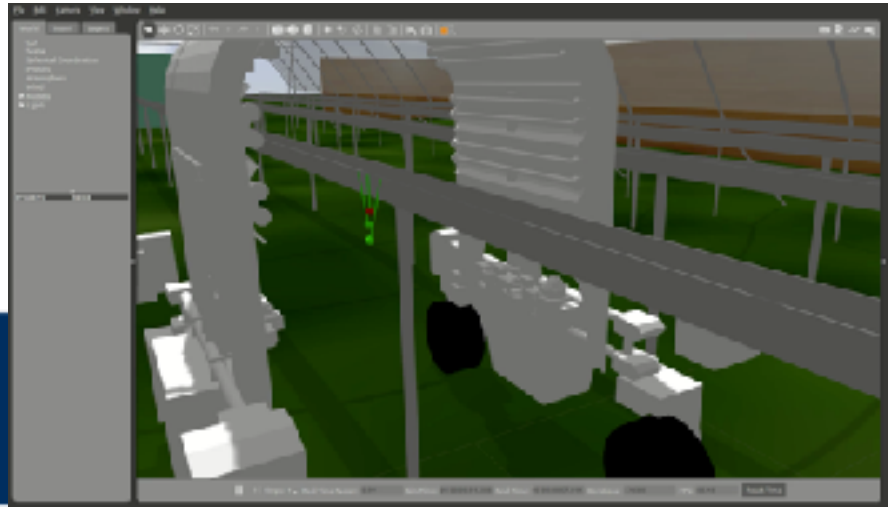
No understanding of the harvesting apparatus perspective.



Picking (Path Planning for Clusters)

- Probabilistic Motion Primitives to deal with Clusters
- submitted to IROS 2020



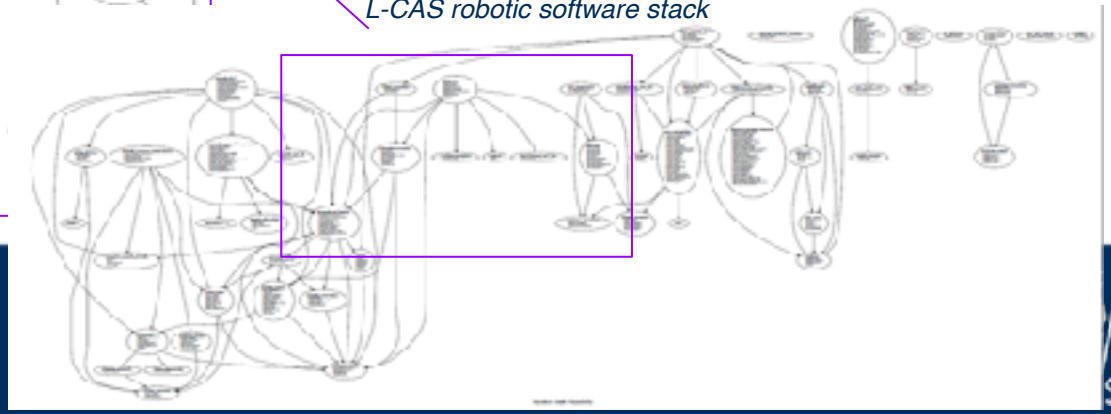


System Integration

- ROS-based Software Infrastructure

RASberry packages

L-CAS robotic software stack



Summary and Future Work

- RASberry - fleet of autonomous robots for soft fruit industry
- Various applications: in-field logistics, plant care, yield prediction, fruit picking
- An *integrated* challenge:
  - logistics needed after picking
  - perception for picking and yield prediction, etc.
  - safely deal with humans in the field