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## Mobile Robotic Strawberry Monitoring and Harvesting in Precision Indoor Farms

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K.C. Ting\*

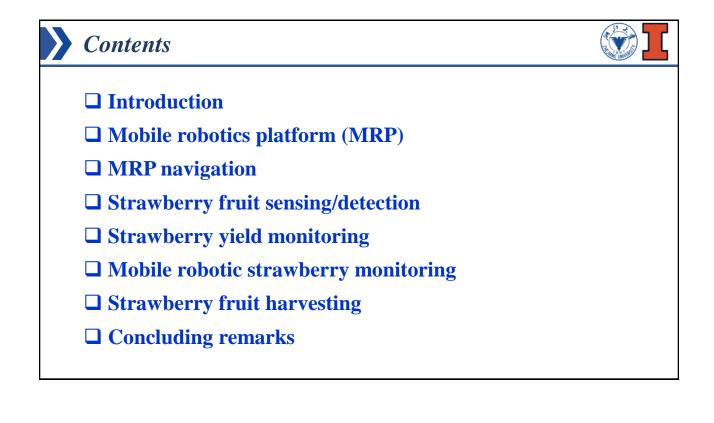
Department of Agricultural and Biological Engineering University of Illinois at Urbana-Champaign (UIUC)

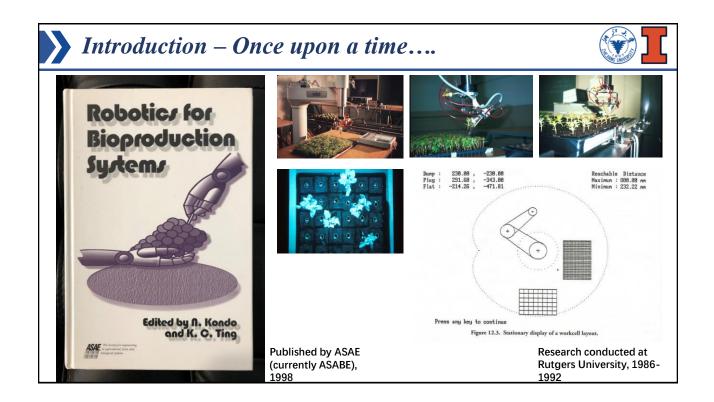
## \*ZJU-UIUC Joint Institute

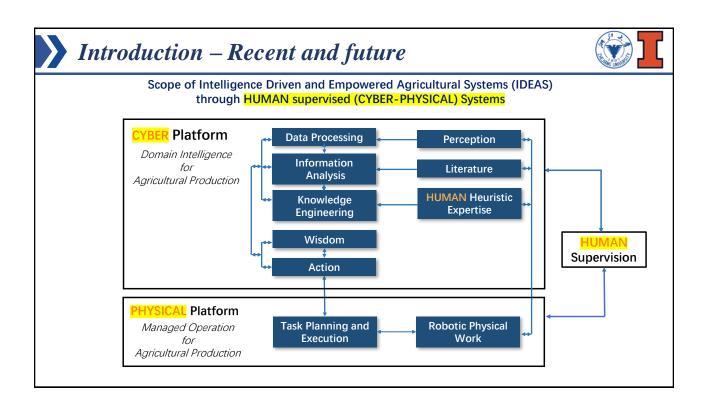
Based on:

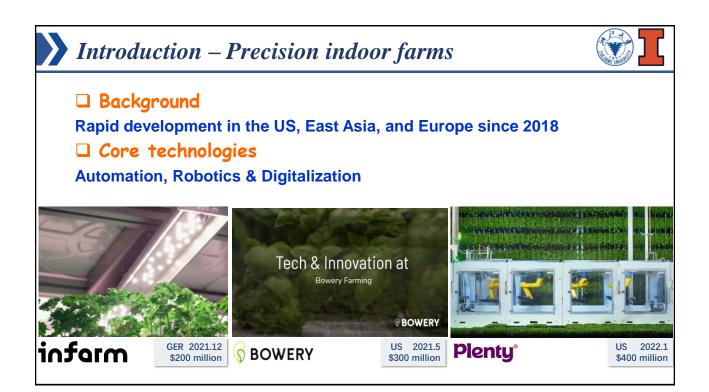
Ren, G., Wu, T., Lin, T., Yang, L., Chowdhary, G., Ting, K.C., Ying, Y. (2023) Mobile robotics platform for strawberry sensing and harvesting within precision indoor farming systems. Journal of Field Robotics, 1-19. <u>https://doi.org/10.1002/rob.22207</u>

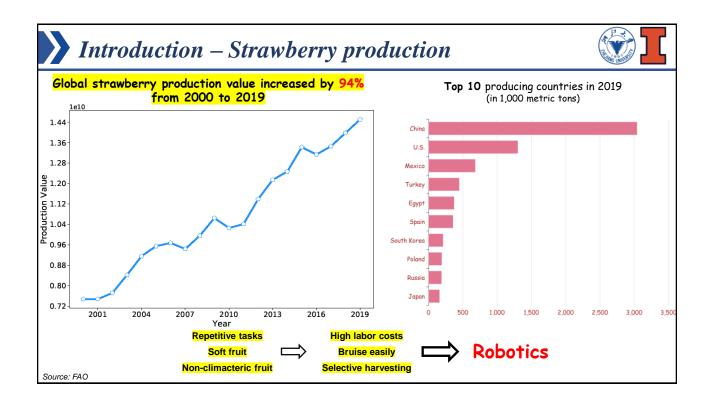
Ren, G., Wu, H., Bao, A., Lin, T., Ting, K.C., Ying, Y. (2023) Mobile robotics platform for strawberry temporal-spatial yield monitoring within precision indoor farming systems. Frontiers in Plant Science 14:1162435. <u>https://doi.org/10.3389/fpls.2023.1162435</u>

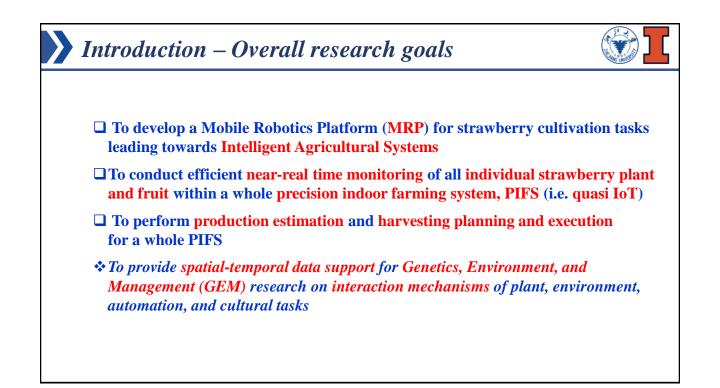


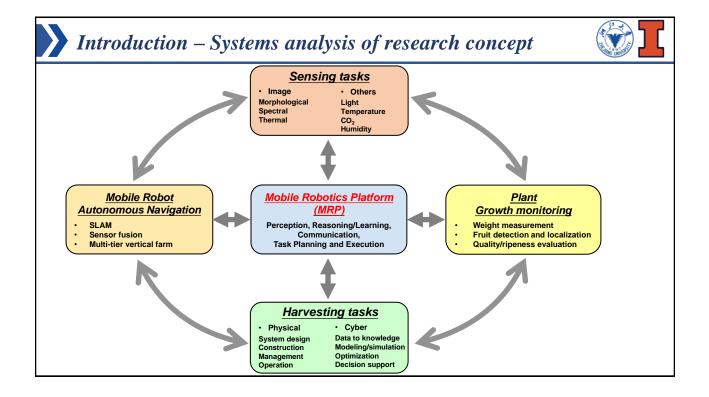


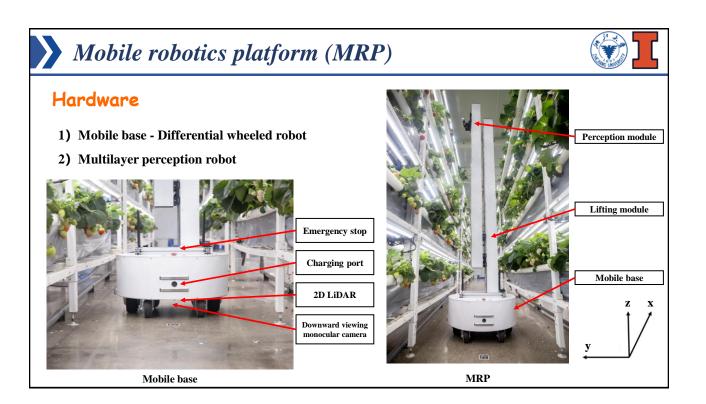












Sensors (Robot Operating System)   Localization: Camera   Obstacle avoidance: 2D LiDAR   2) Operating system Obstacle Detection Node   5 ROS nodes Camera   Output: Target velocity   3) Low-level control system Navigation Node	MRP navigatio	on		
1) Sensors (Robot Operating System) Low-level Control System   Localization: Camera+IMU+Encoders Obstacle avoidance: 2D LiDAR 2D LiDAR Obstacle Detection Node Obstacle information   2) Operating system 5 ROS nodes Camera Localization Node State Machine Node Low-level Control System   5 ROS nodes Output: Target velocity IMU Localization Node System state Low-level Control Board Control Board   3) Low-level control system Output: 2 motor speeds Wheel Encoders Navigation Node Target velocity Low-level	Navigation system	l		
Obstacle avoidance: 2D LiDAR 2) Operating system 5 ROS nodes Output: Target velocity 3) Low-level control system Output: 2 motor speeds Camera Mavigation Node Obstacle Detection Node Camera Localization Node Navigation Node Navigation Node Camera Navigation Node Camera Navigation Node Camera Navigation Node Camera Navigation Node Camera Navigation Node Control Board Control Board Control Board Control Board Control System Control	1) Sensors			Low-level Control System
2) Operating system 5 ROS nodes Output: Target velocity 3) Low-level control system Output: 2 motor speeds Output: 2 motor speeds	Localization: Camera+IMU+Encod	lers		
5 ROS nodes Output: Target velocity 3) Low-level control system Output: 2 motor speeds Camera Localization Node Localization Node Navigation Node Localization Navigation Node Localization Node Localization Node Localization Localization Node Localization Localization System state Control Board Right Control System Right Control System System State Control System Control System Contro	Obstacle avoidance: 2D LiDAR	2D LiDAR		Emergency Stop
5 ROS nodes Output: Target velocity 3) Low-level control system Output: 2 motor speeds Output: 2 motor speeds	2) Operating system		State Machine Node	
Output: Target velocity 3) Low-level control system Output: 2 motor speeds	5 ROS nodes	Camera		
Output: 2 motor speeds	Output: Target velocity	IMU —		
Output: 2 motor speeds	3) Low-level control system		Navigation Node	Right Motor
Navigation system architecture	Output: 2 motor speeds	Wheel Encoders	Communication Node	Controller
Navigation system architecture				i
			Navigation system architecture	

## • MRP navigation

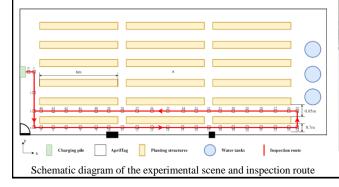


## Navigation approach - AprilTag and Inertial based navigation (ATI navigation)

### 1) Mapping

Data fusion: AprilTag + IMU + Wheel encoders

- 2) Path planning Breadth-first search (BFS) algorithm
- 3) Control PID controller + Differential motion model





The MRP is being charged in the commercial strawberry factory

# MRP navigation

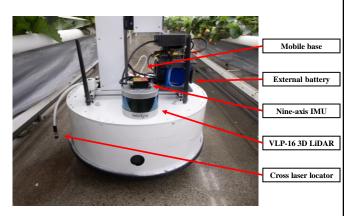
## Experiments

### 1) Objectives

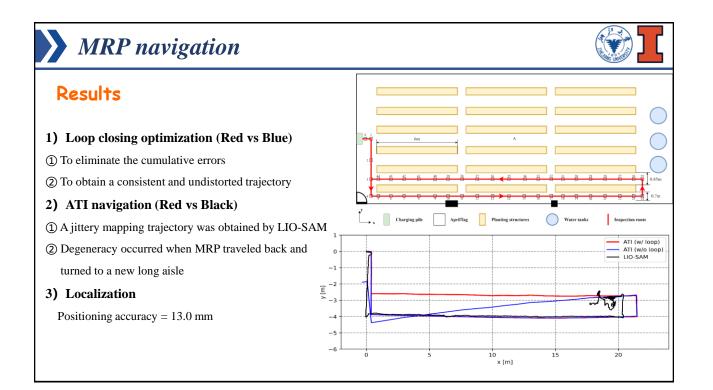
- (1) The impact of loop optimization on ATI navigation
- (2) The advantage of ATI navigation in PIFs
- 2) Methods
- (1) LIO-SAM (Tightly coupled Lidar-Inertial odometry)
- (2) ATI navigation w/o loop optimization
- 3 ATI navigation w/ loop optimization

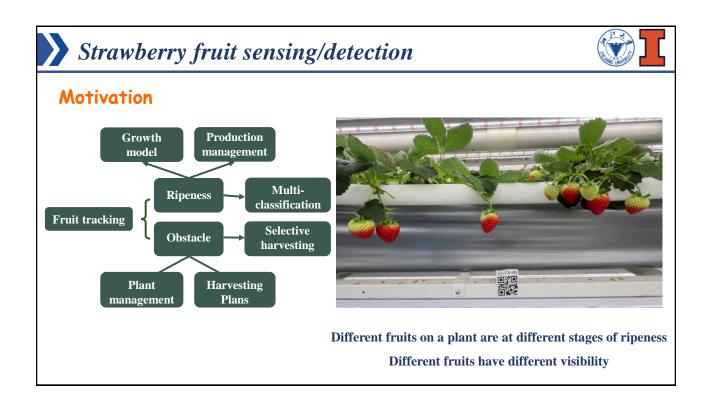
#### 3) Evaluation

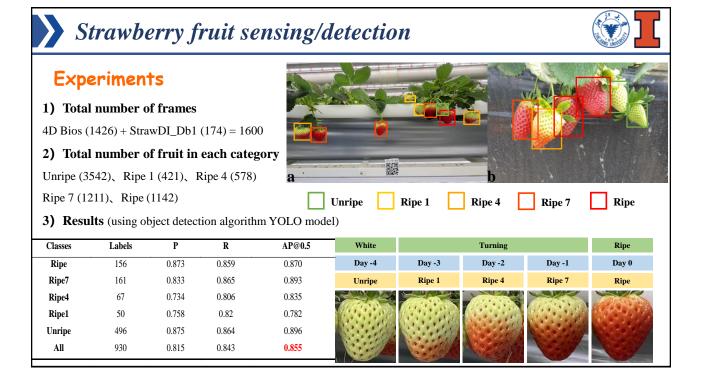
Mapping trajectories

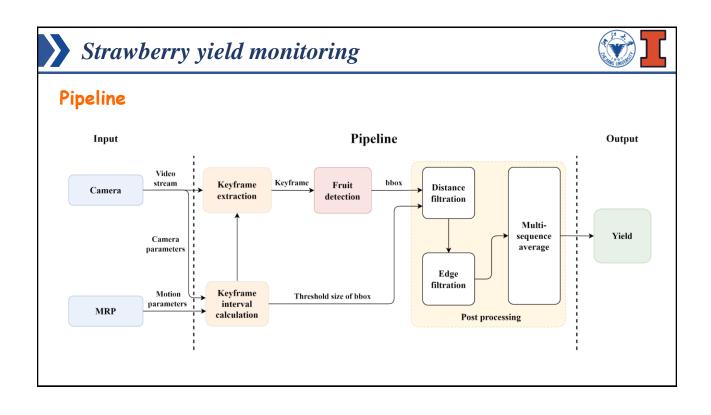


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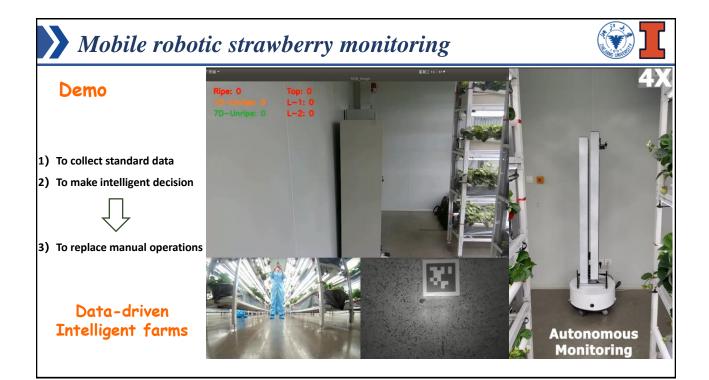


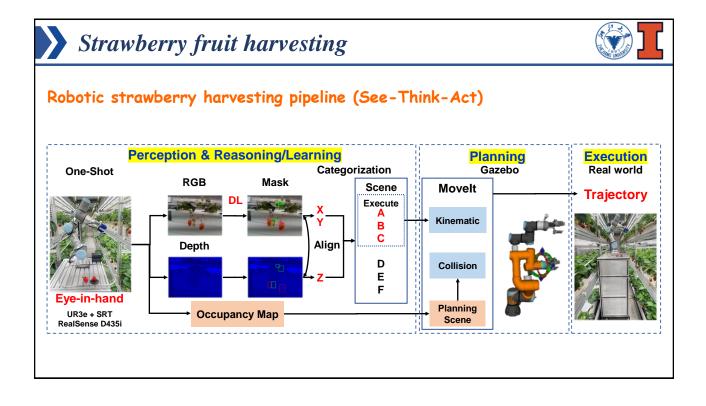


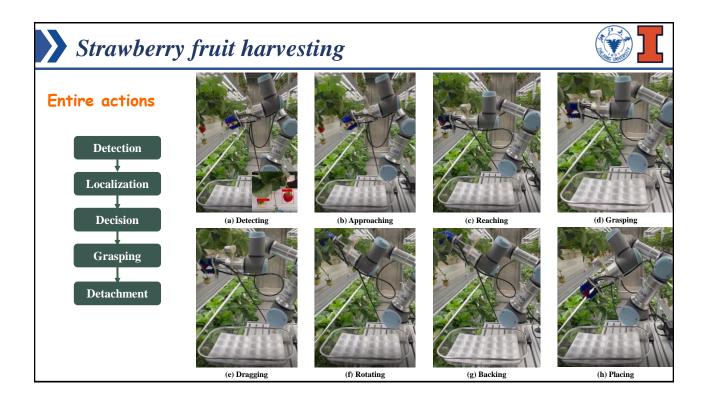
## Strawberry yield monitoring Counting-from-video problem (a) r = 21) Motivation (b) r = 3To determine the frame interval between keyframes (i)by fixing the number of counts for the same fruit (r)(c) r = 42) Formulation Example series of keyframes at various values of r. (1) Pixel distance of two neighboring keyframes $(d_p) \rightarrow$ Movement of MRP (2) Assuming the speed of MRP (v), average distance between camera and fruit (d), frame rate of video (fps) to be constant (3) To calculate the theoretical interval of keyframes $(i_t)$ , take the nearest integer of $i_t$ as the actual interval of keyframes (i)

 $\begin{array}{l} w \text{ was the image width} \qquad d_p = \frac{w}{r} \\ f_x \text{ was camera's intrinsic parameter} \\ i_t = \frac{d_p \times d \times fps}{f_x \times v} \end{array} \end{array} \right\} \quad i = int(i_t) = int\left(\frac{w \times d \times fps}{f_x \times v \times r}\right) \longrightarrow \quad i = g(v \times r) \\ \\ \begin{array}{l} \text{Statistics of fruit detection results of} \end{array} \right)$ Statistics of fruit detection results of keyframes

Experiments	e was the absolute difference between i and i <sub>t</sub> T was the tier number of growing unit											
-	Setup				Video	n				<b>A</b>	4	
-	v (m/s)	r	i	е	ID	T1	T2	T3	T4	_ Avg err <sup>c</sup>	Avg err	
	0.2	15	3	0.044	1	34	52	87	70	0.0265	0.0626	
1) Goal	0.2	9	5	0.073	2	35	55	88	69	0.0265	0.0626	
Yield monitoring accuracy under		15	2	0.029	1	37	54	88	71			
different speeds of MRP	0.3	10	3	0.044						0.0229	0.0905	
2) Counting (i.e. monitoring) error ra $err^{c}$ : 2% ~ 3%	ate	6	5	0.073	2	36	53	90	72			
······	0.4	11	2	0.075	1	37	51	85	71	0.0252	0.0711	
<b>3)</b> Yield (i.e. detection + monitoring)		<b>0.4</b> 6	6	4	0.195	2	38	52	84	70	0.0252	0.0711
error rate			$n_{GT}^C$	,		36	54	85	70			
$err^{Y}$ : 6% ~ 10%			$n_{GT}^Y$			32	51	83	65			







# Strawberry fruit harvesting

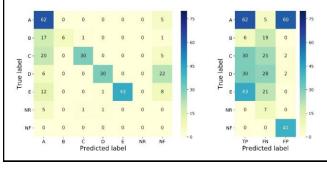
Rule-based approach to strawberry scene categorization for performing executable harvesting actions

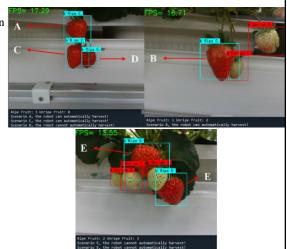
### Dataset

- The fruit growth scene categorization test set included **160** images in the strawberry ripeness test set, with 269 ripe and 213 unripe ones.
- A: 67, B: 25, C: 55, D: 58, E: 64

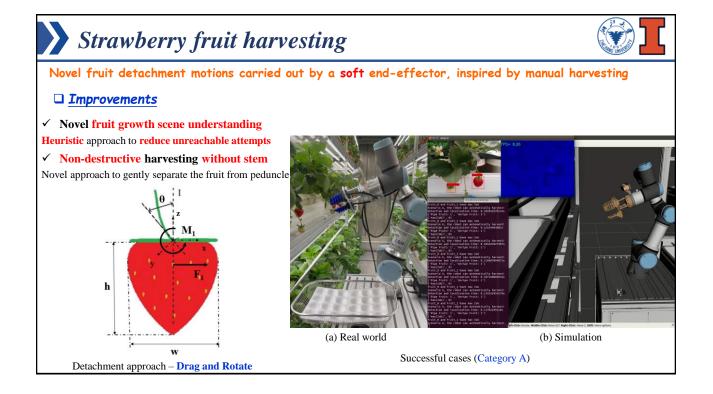
## Conclusion

For all, Accuracy = 89.1% Micro F1-score = 0.7For scenario E, Accuracy = 92.4% Micro F1-score = 0.8





Samples of fruit growth scene categorization results



# Strawberry fruit harvesting

□ Failure case

## **Results**

## □ Success rate

- For all Success rate = 78%

- For scenario A

Success rate = 88%

### 

				Detection		Grasping		hment	Placement	Overall		
	Scenarios	Amount	S	Т	S	Т	S	Т	Т	S	D	Т
			/%	/ms	/%	/s	/%	/s	/s	/%	/%	/s
26.9%	А	52	98	96	96	4.2	88	2.8	3.4	88	23	10.5
	В	16	94	99	88	4.1	63	2.8	3.4	63	25	10.5
	С	18	94	98	89	4.1	72	2.8	3.4	72	22	10.4
	D	14	93	96	93	4.1	64	2.8	3.4	64	21	10.4
etachment acement	All	100	96	97	94	4.2	78	2.8	3.4	78	23	10.5

## (1) Fruit B was mistakenly detected as Fruit A, causing detachment to fail. (2) Fruits C and D were mistakenly detected as A, causing localization to fail.

3 When harvesting Fruit C, Fruit D (A) was affected to fail in grasping and detachment.



