AuSRoS

Australian School of Robotic Systems

D1 – Why Simulation in Robot Learning?

Prof Tat-Jun (TJ) Chin

Lectorial D1 @ AuSRoS
Why Simulation in Robot Learning?

Prof Tat-Jun (TJ) Chin, www.ai4space.group

Australian Institute for Machine Learning

Outline

- Track D: Robot Learning
- Motivation - why simulation in robot learning?
- Recap on imitation learning
- Recap on object pose estimation
- Popular simulators

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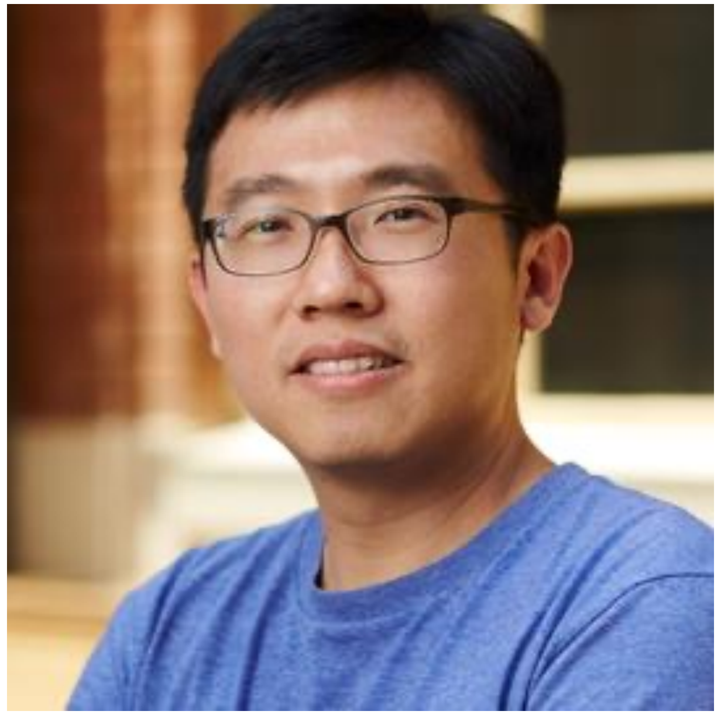
Track D: Robot Learning

Prof Tat-Jun Chin (www.ai4space.group)
SmartSat CRC Professorial Chair of Sentient Satellites
Australian Institute for Machine Learning, Adelaide



Lectorial D1: Simulation in Robot Learning
Lectorial D2: Bridging the Reality Gap

Dr Feras Dayoub (https://ferasdayoub.com/)
Senior Lecturer
Australian Institute for Machine Learning, Adelaide

Lectorial D3: Foundation Models in Robot Learning

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BBC

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Chandrayaan-3: Historic India Moon mission sends new photos of lunar surface

7 August 2023

Share

By Geeta Pandey, BBC News, Delhi

A series of images sent by Chandrayaan-3 show the craters on the lunar surface getting larger and larger as the spacecraft gets closer

India's space agency has released the first images of the Moon taken by the Chandrayaan-3 spacecraft, which entered lunar orbit on Saturday.

BBC

Home News Sport Business Innovation Culture Travel Earth Video Live

Japan: Moon lander Slim comes back to life and resumes mission

29 January 2024

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By Kelly Ng, BBC News

Jaxa produced this render of Slim to show the awkward landing orientation that pointed the solar cells away from the Sun

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Intuitive Machines lands on the moon

Jeff Foust February 22, 2024

An image released by Intuitive Machines after its Nova-C lander entered lunar orbit Feb. 21 on the IM-1 mission. Credit: Intuitive Machines

NSF

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China Roundup: Chang'e 6 lands on the Moon, and record-breaking EVA

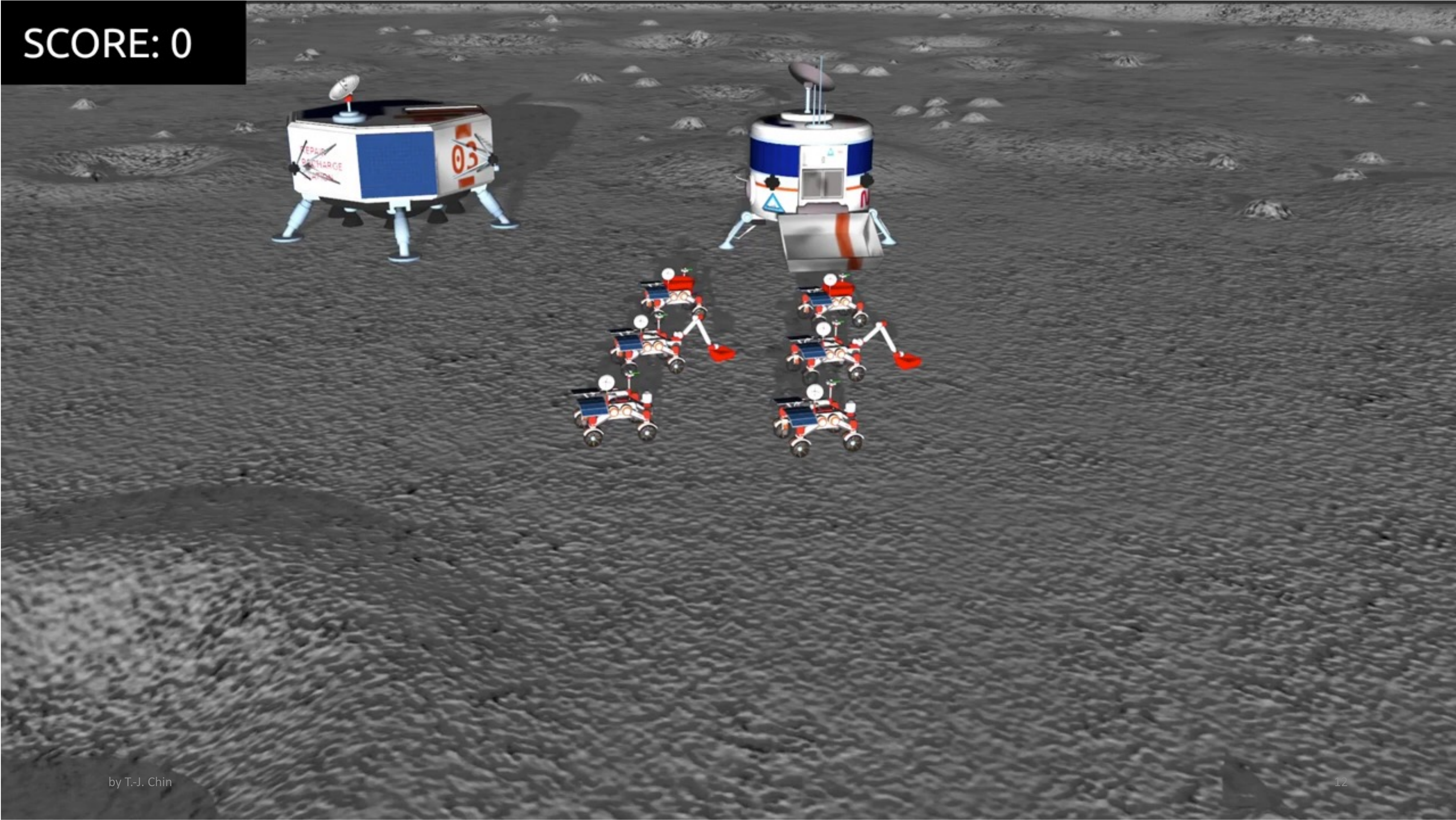
written by Martijn Luinstra | June 9, 2024

China's Chang'e 6 landed on and sampled the far side of the Moon while the Shenzhou-18 crew performed a record-breaking spacewalk at the Tiangong Space Station. Additionally, 10 more rockets were launched from the country in the last few weeks.

by T.-J. Chin

Crater Lab @ UoA Exterres Analogue Facility

Andy Thomas Centre for Space Resources
The University of Adelaide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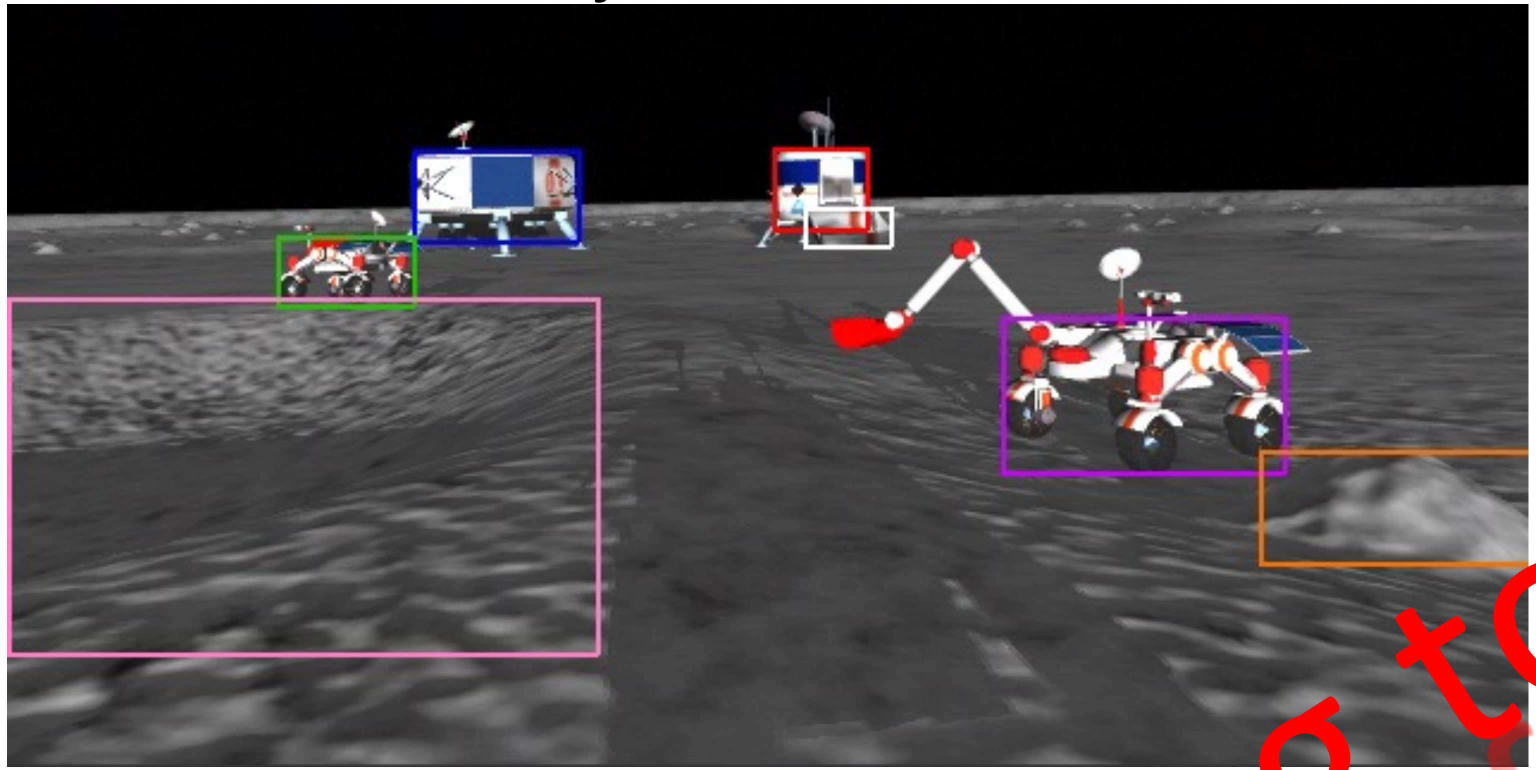
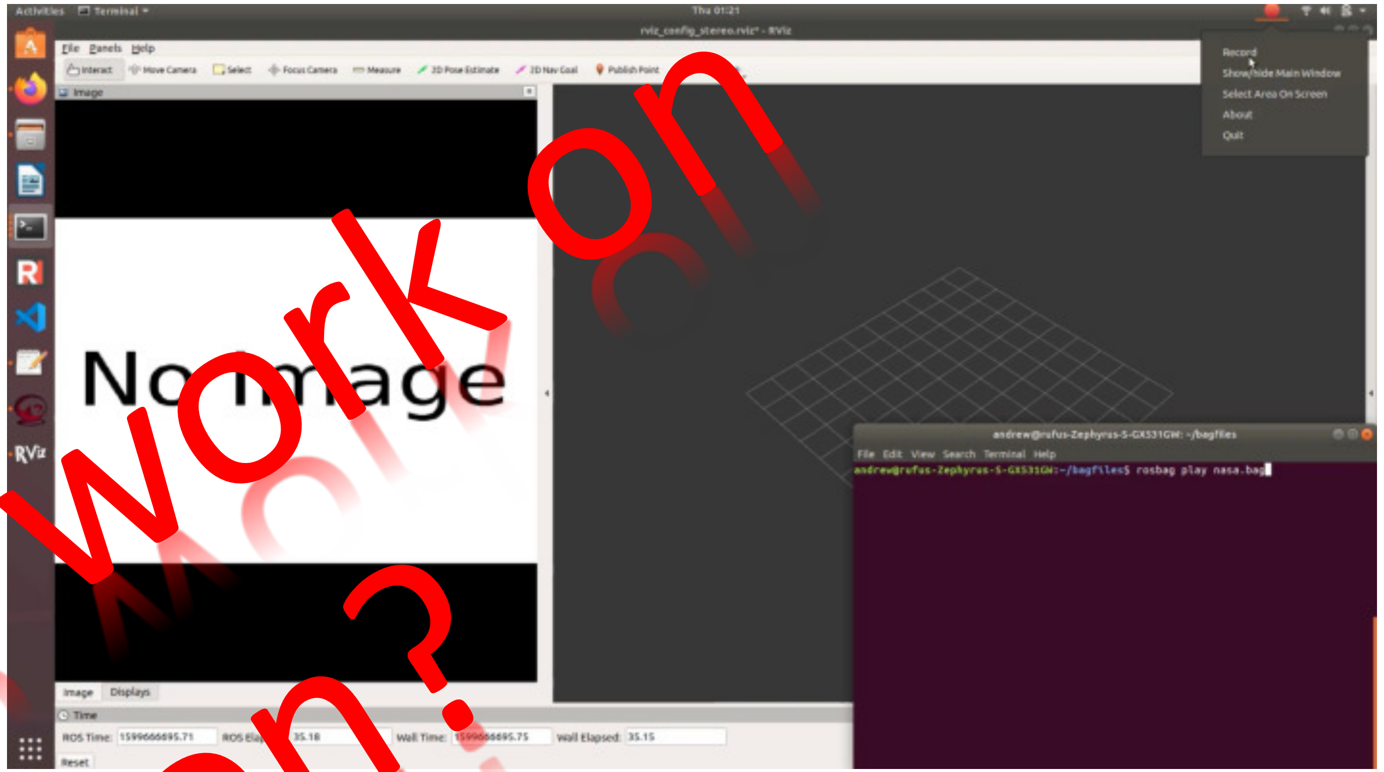
Object detection



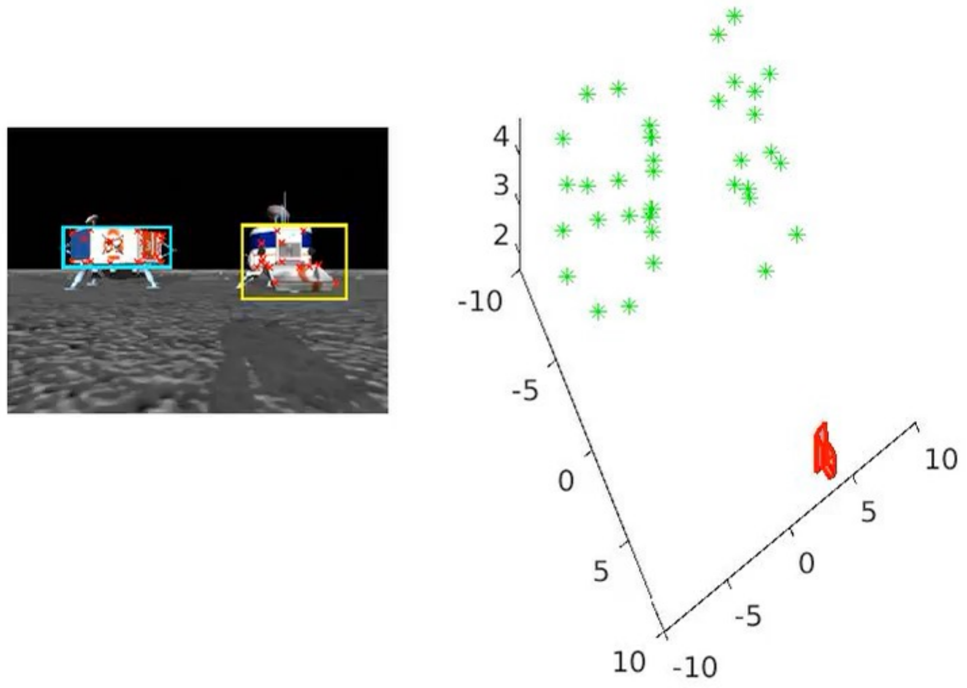
Visual SLAM



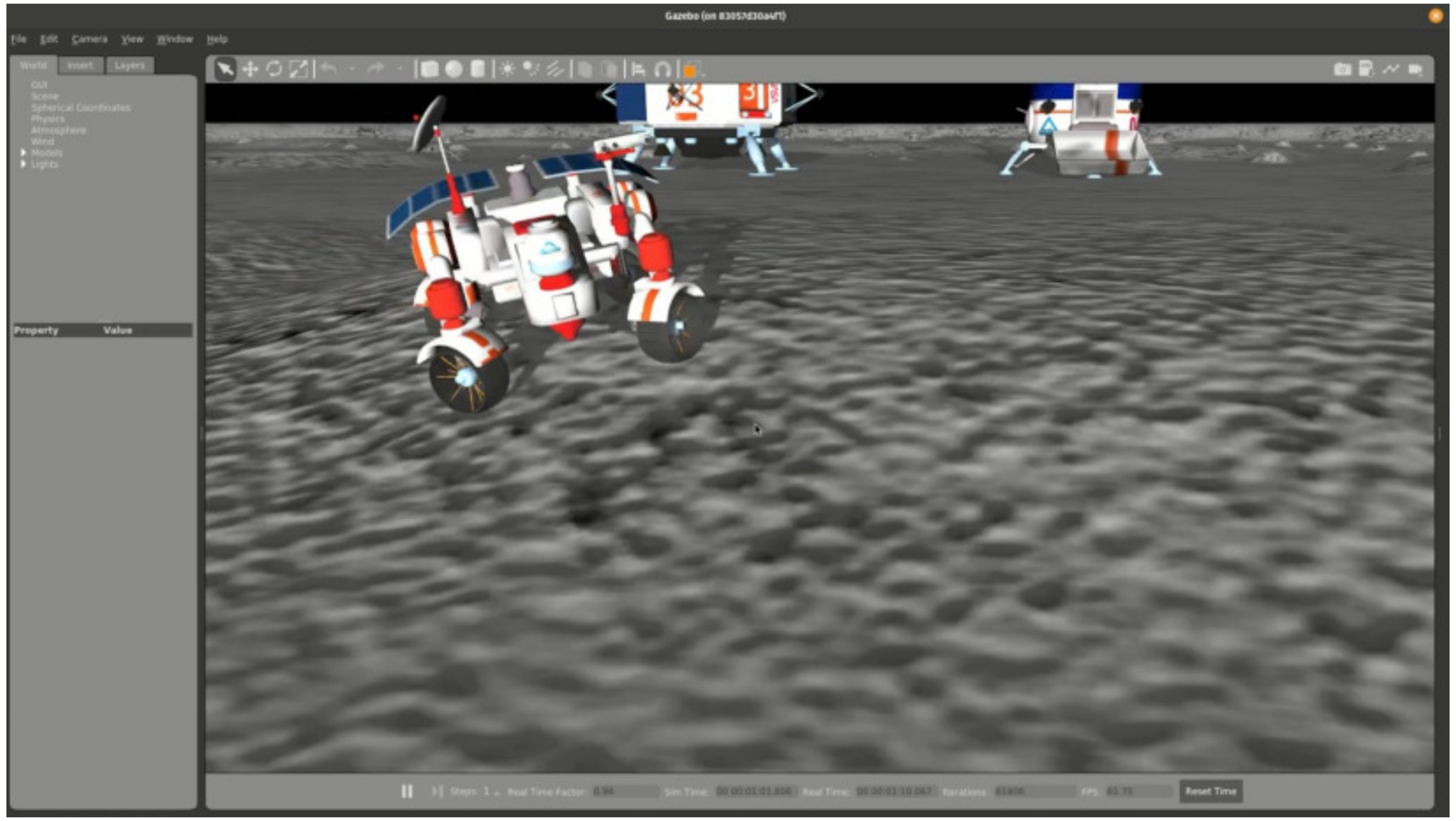
Is it going to work on the Moon?

Locomotion, obstacle avoidance, path planning

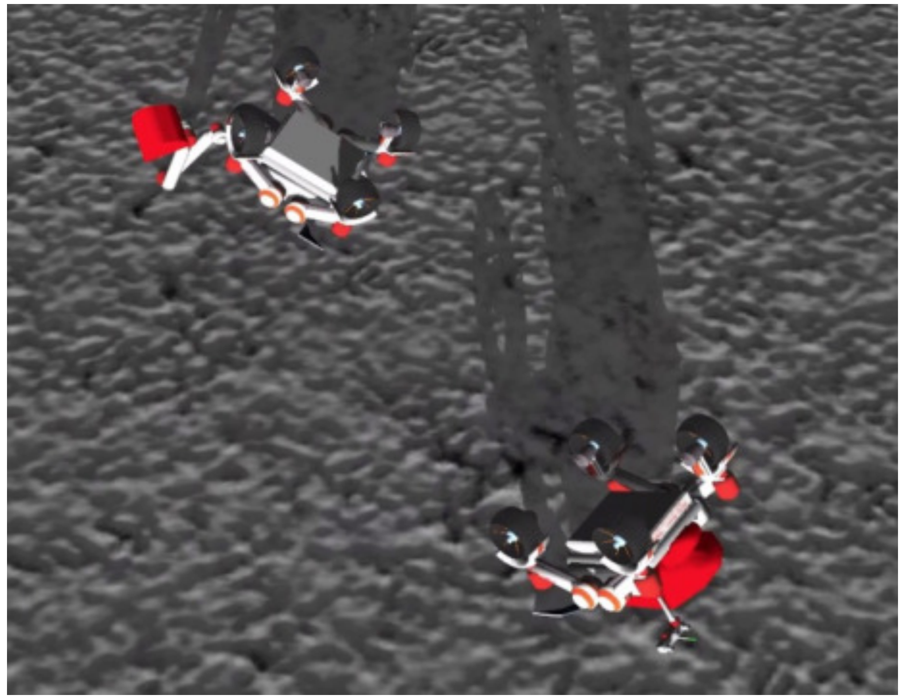
Place recognition by pose estimation



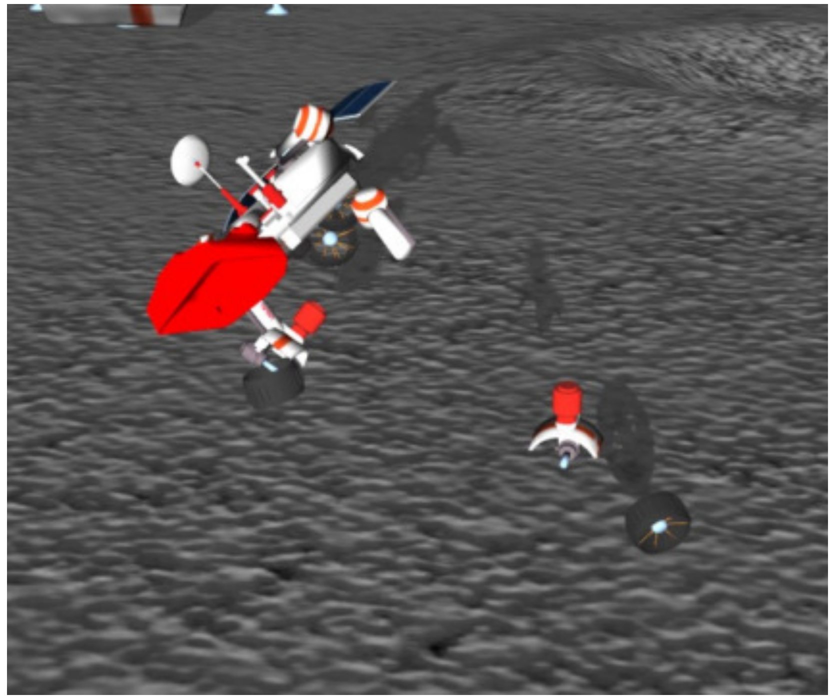
Simulating physical dynamics



- Wheel slippage.
- Noisy wheel odometry.



- Collisions and damage.

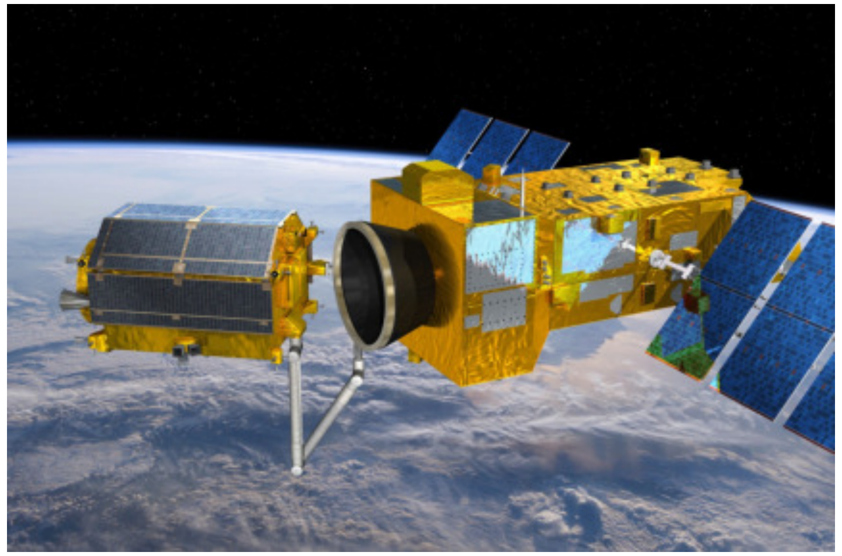


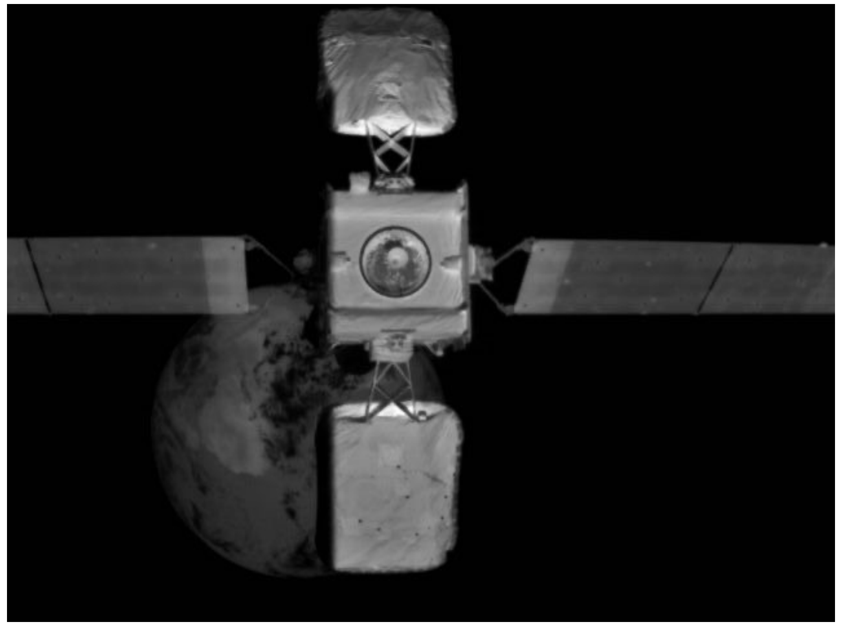
- Wear and tear.

Spacecraft rendezvous and docking

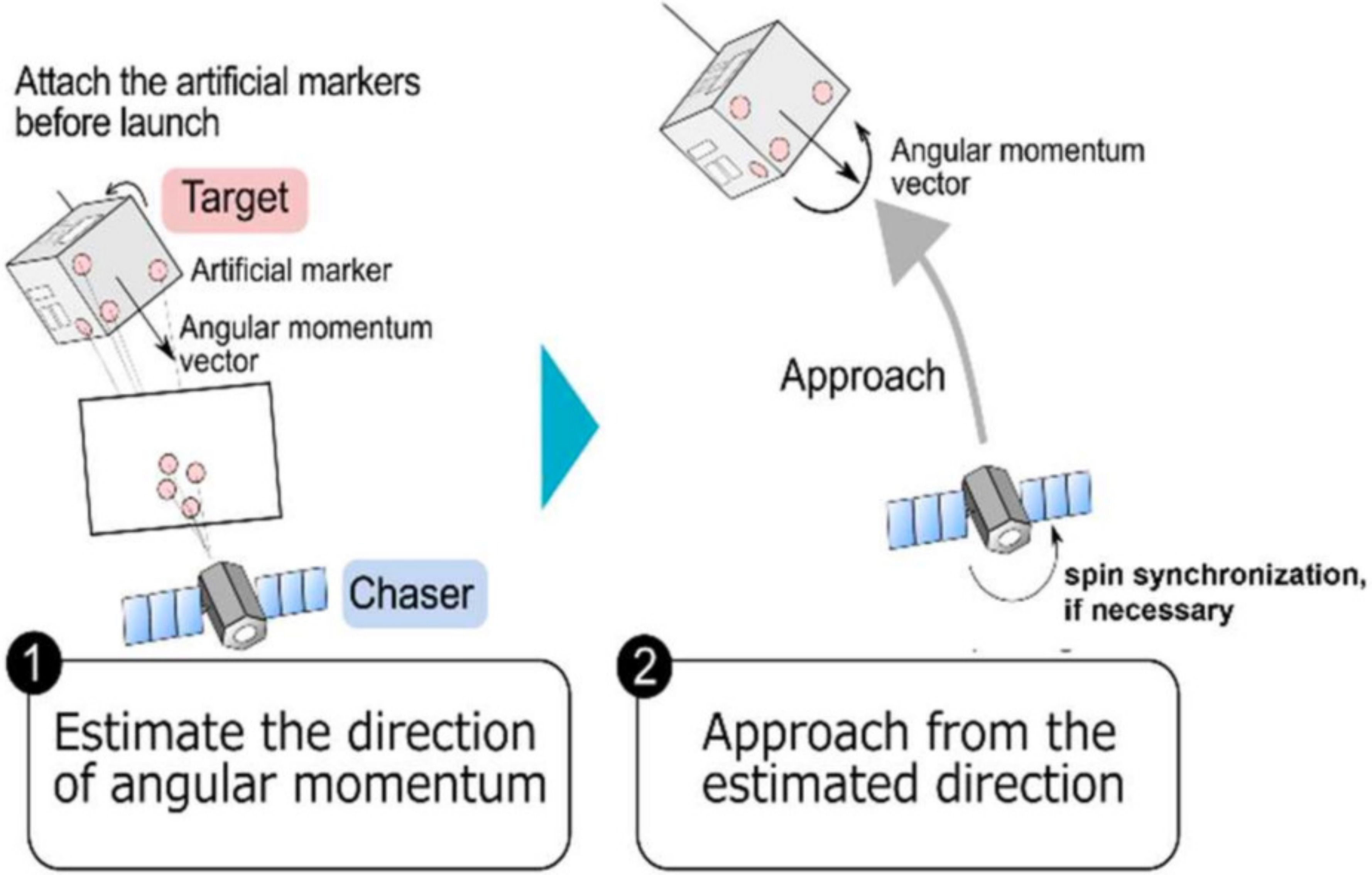
https://astroscale.com/historic-approach-to-space-debris-astroscales-adras-j-closes-in-by-50-meters/

Robotic vision for spacecraft rendezvous





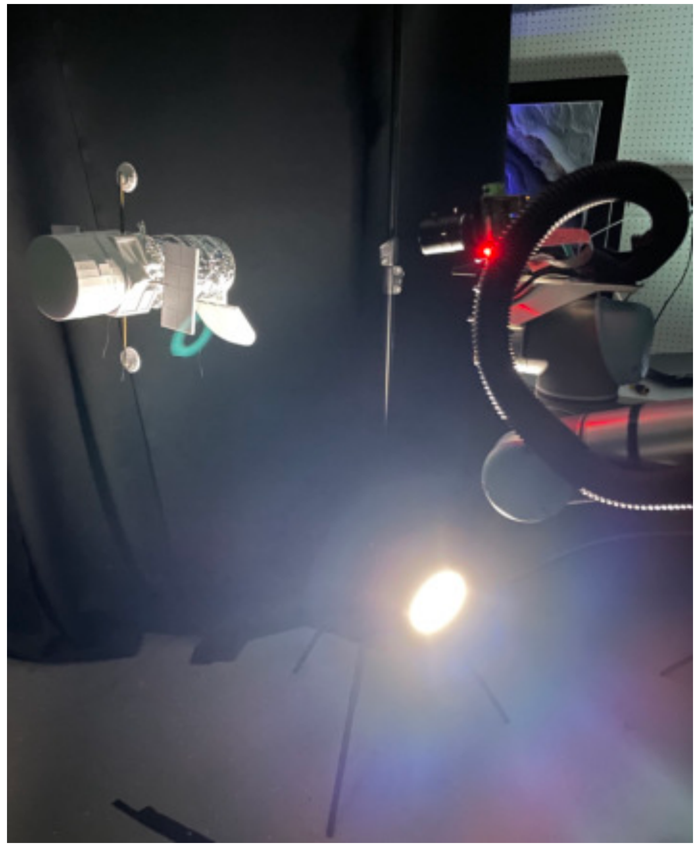
https://news.northropgrumman.com/news/releases/northrop-grumman-and-intelsat-make-history-with-docking-of-second-mission-extension-vehicle-to-extend-life-of-satellite

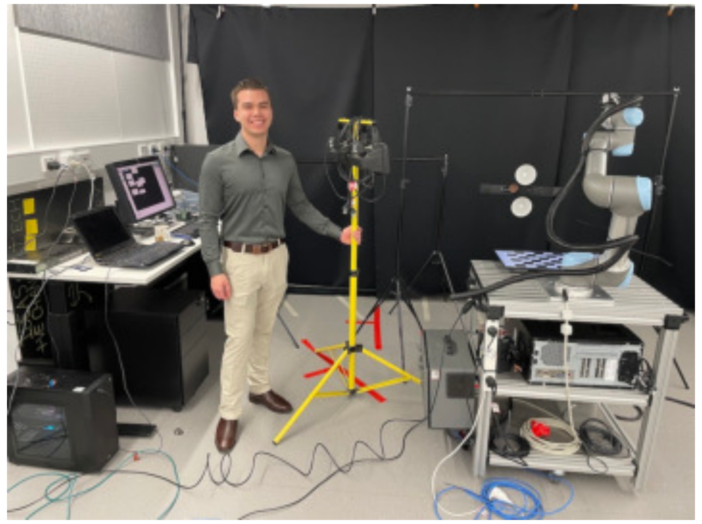


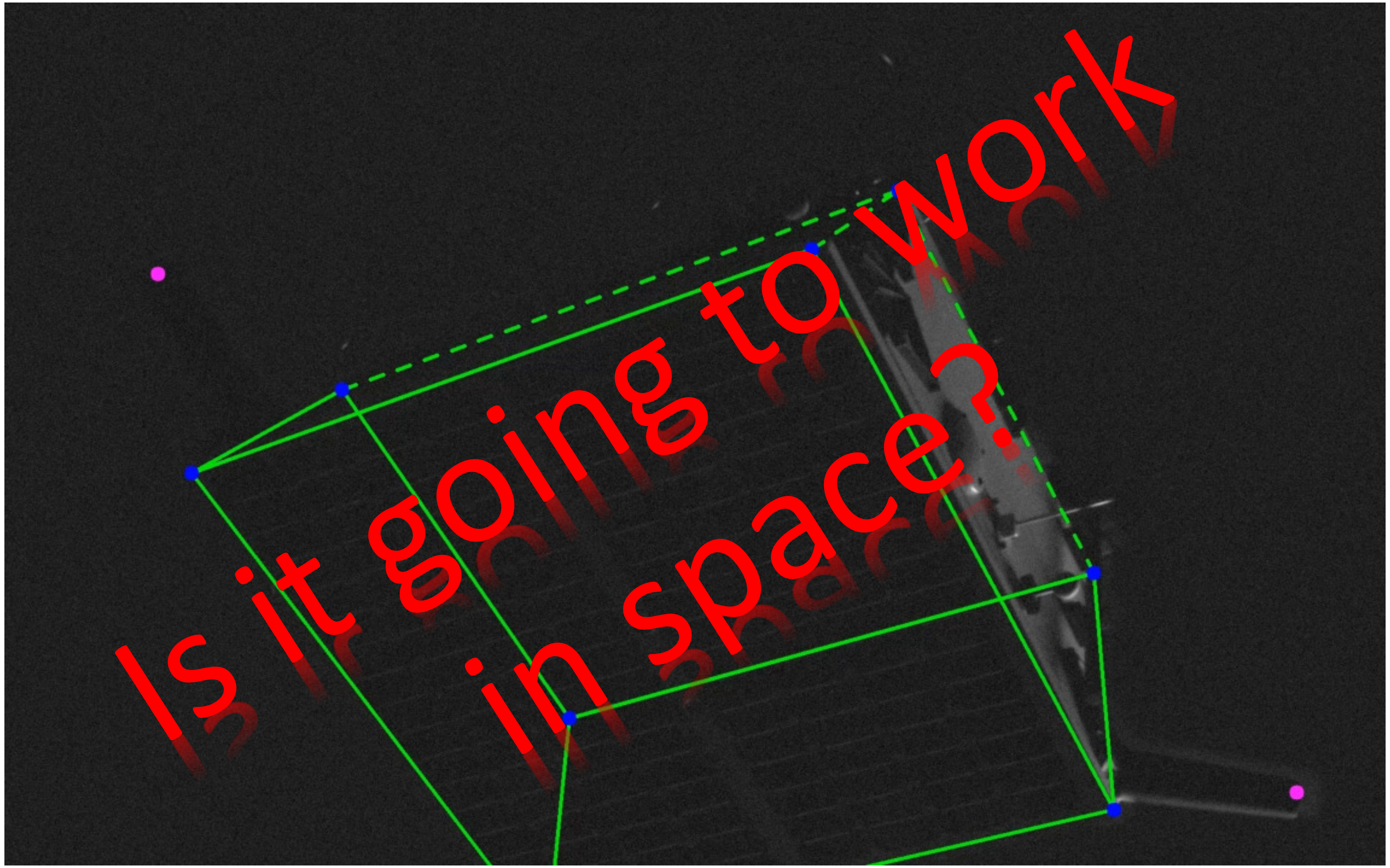
Kawaguchi and Kusumoto, ALGEBRAIC AND SIMULTANEOUS ESTIMATION OF ATTITUDE MOTION AND INERTIA PROPERTIES FOR INNOVATIVE SPACE DEBRIS REMOVAL

Hardware-in-the-loop emulator

Source: https://www.youtube.com/@mohsi.j







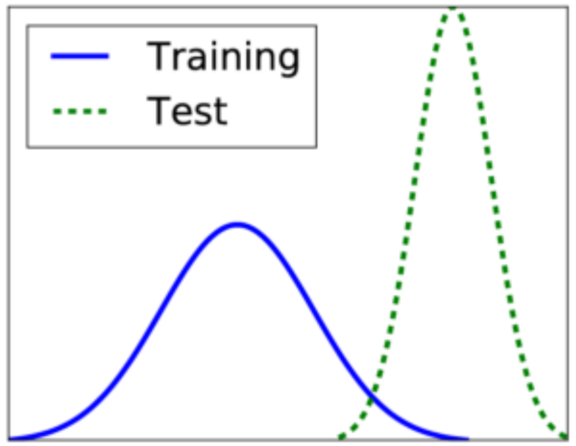
Bo Chen, Jiewei Cao, Álvaro Parra Bustos, Tat-Jun Chin: Satellite Pose Estimation with Deep Landmark Regression and Nonlinear Pose Refinement. ICCV Workshops 2019: 2816-2824

Tae Ha Park, Marcus Märtens, Mohsi Jawaid, Zi Wang, Bo Chen, Tat-Jun Chin, Dario Izzo, Simone D'Amico. Satellite pose estimation competition 2021: Results and analyses. Acta Astronautica. Volume 204 Pages 640-665.

Domain gap

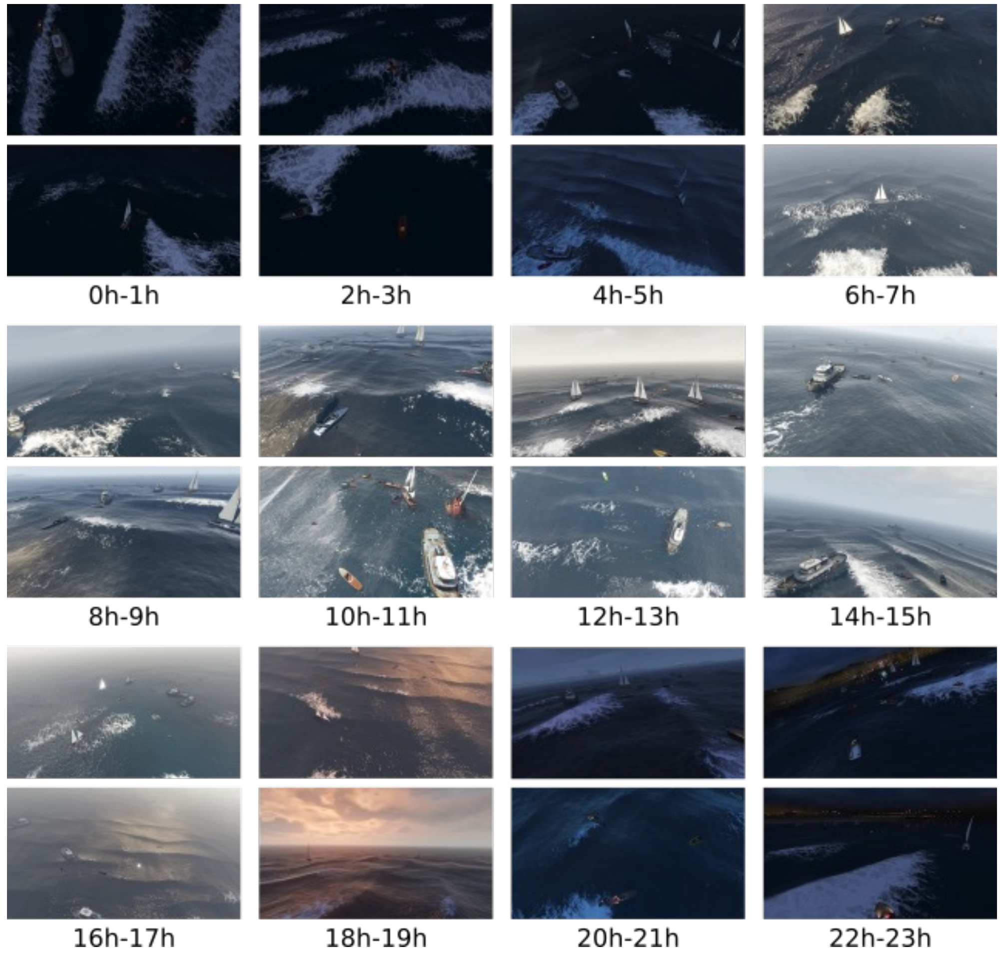
- Let $\mathcal{D} = \{(x_i^{\mathcal{S}}, y_i^{\mathcal{S}})\}_{i=1}^N$ be a labelled training dataset assumed drawn from a **source domain distribution** $P_{XY}^{\mathcal{S}}$. The space of labels is denoted $\mathcal{Y}^{\mathcal{S}}$, i.e., $y_i^{\mathcal{S}} \in \mathcal{Y}^{\mathcal{S}}$ for all i.
- Let $\mathcal{E} = \{x_j^{\mathcal{T}}\}_{j=1}^M$ be an unlabelled testing dataset with true labels $\mathcal{L} = \{y_j^{\mathcal{T}}\}_{j=1}^M$, where $\mathcal{Y}^{\mathcal{T}}$ is the label space, i.e., $y_j^{\mathcal{T}} \in \mathcal{Y}^{\mathcal{T}}$ for all j. We assume that $\{(x_j^{\mathcal{T}}, y_j^{\mathcal{T}})\}_{j=1}^M$ is drawn from a **target domain distribution** $P_{XY}^{\mathcal{T}}$.
- The goal of supervised learning is to train a model f_θ from $\mathcal{D}$, such that the error between the predictions $f_\theta(x_j^{\mathcal{T}})$ and true labels $y_j^{\mathcal{T}}$ is as small as possible.
- We say there is a **domain gap** (domain shift, covariate shift, etc.) between the source and target domains if

$$P_{XY}^{\mathcal{S}} \neq P_{XY}^{\mathcal{T}}$$



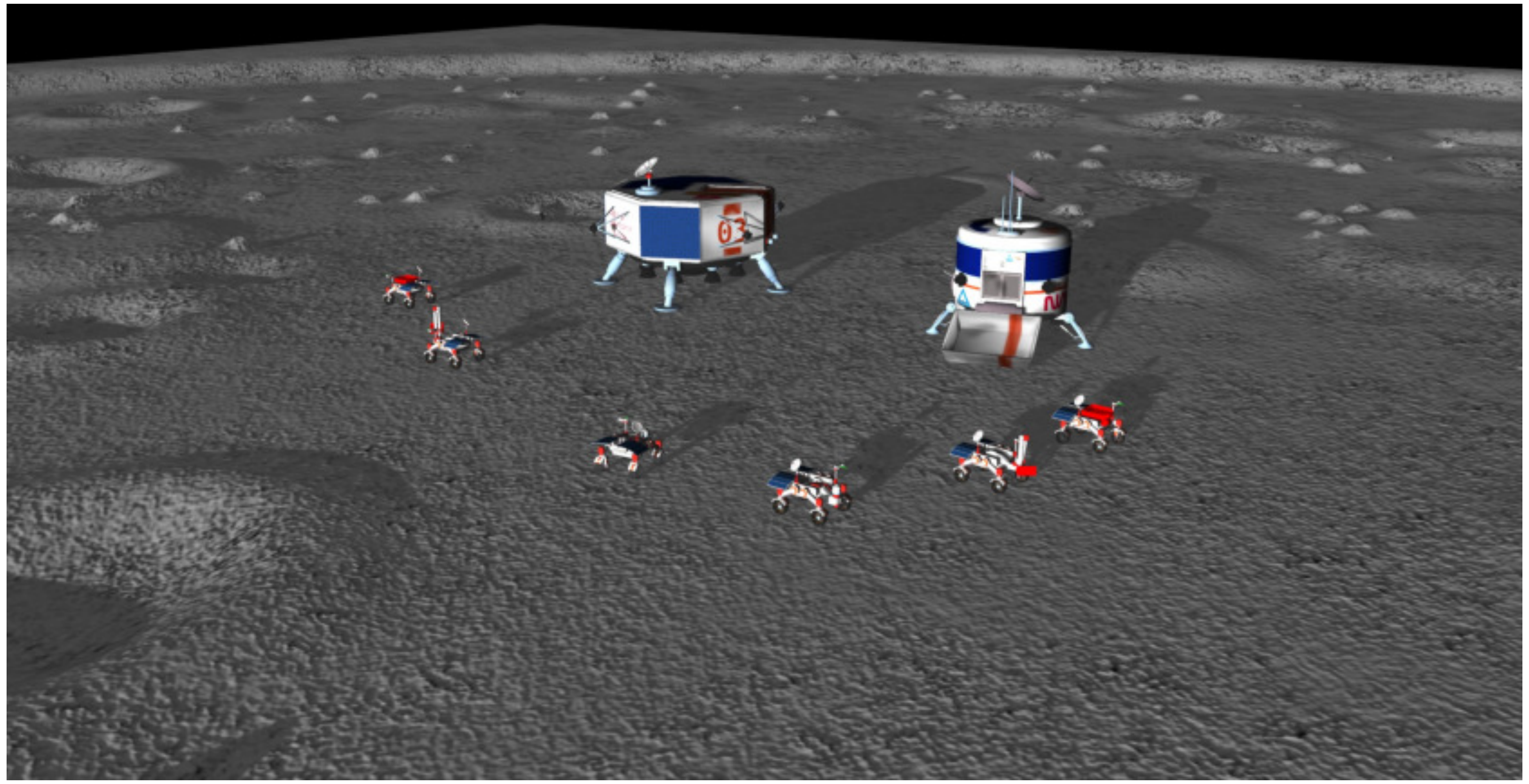
Causes of domain gap

- Different operating environments (simulation vs real, Tokyo vs Paris, etc.).
- Different environmental conditions (day vs night, sunny vs rainy, summer vs winter, etc.).
- Dynamic operating environments (things moved, construction, changed traffic flows, etc.)
- Different sensors or sensor drift (Intel Realsense vs FLIR, Prophesee vs Inivation, etc.).
- **Combination of the above.**

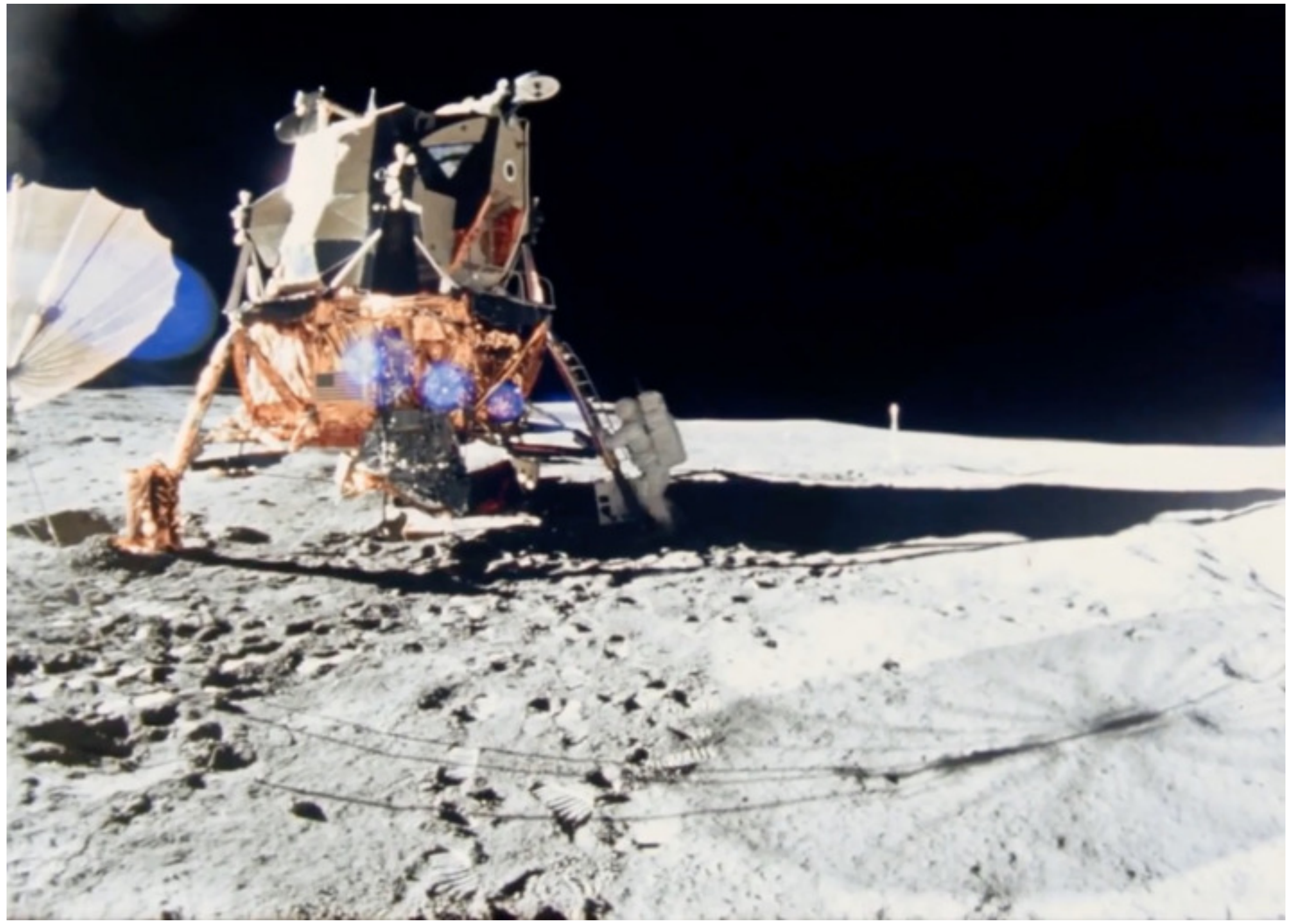


Sim2real gap (a.k.a. reality gap)

- A special case of domain gap where the source domain is synthetically generated and the target domain is the real operating environment.



Gazebo simulation

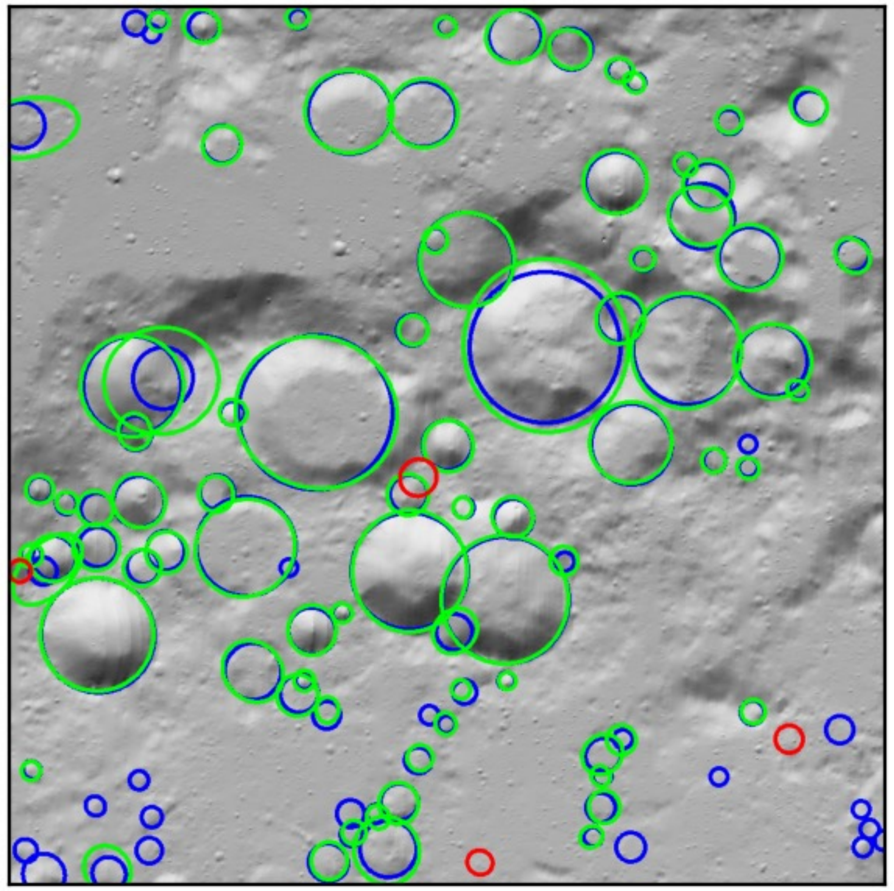


Apollo 14

Negative effect of sim2real gap

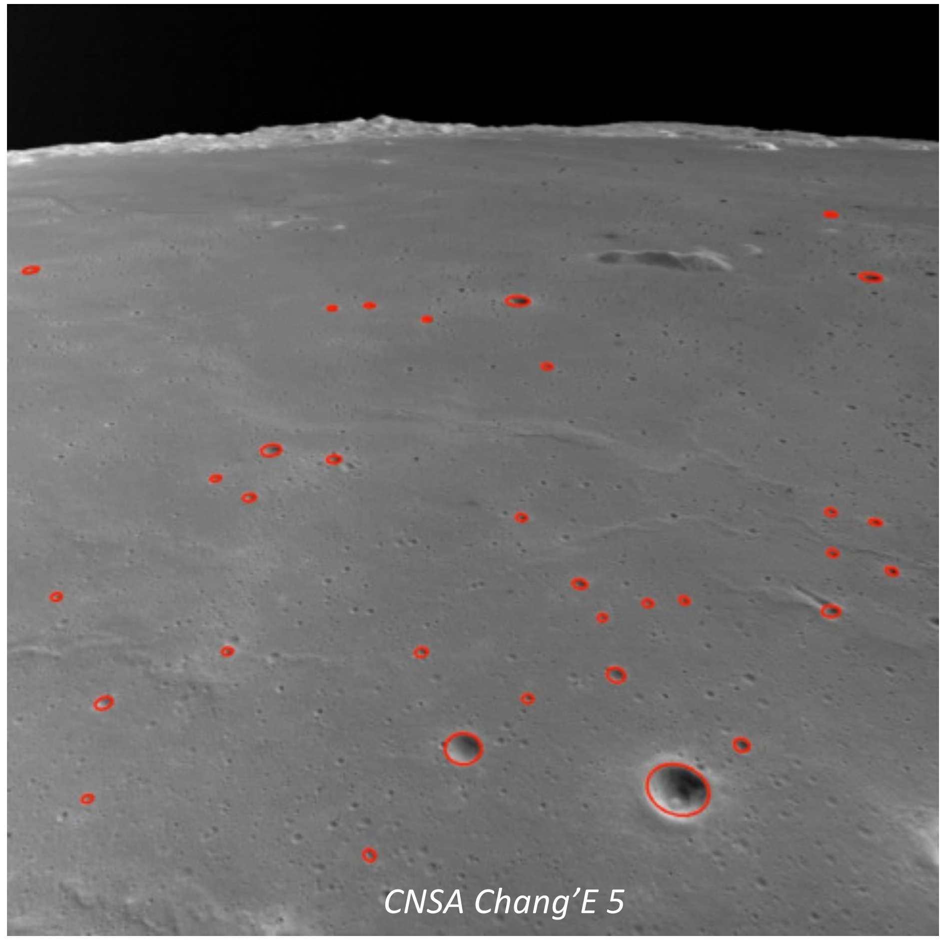
Train on synthetic, test on synthetic

CDA	Precision	Recall	F1-Score
Ellipse R-CNN	**86.5%**	**75.7%**	**80.8%**
Mask R-CNN	78.7%	65.5%	71.5%



Train on synthetic, test on real

CDA	Precision	Recall	F1-Score
Ellipse R-CNN	56.8%	**58.7%**	**55.9%**
Mask R-CNN	**58.1%**	50.9%	54.2%



Matthew Rodda, Sofia McLeod, Ky Cuong Pham, and Tat-Jun Chin. (2024). Camera-Pose Robust Crater Detection from Chang'e 5. arXiv:2406.04569v1 [cs.CV] 07 Jun 2024
Sofia A McLeod et al., Robust Perspective-n-Crater for Crater-based Camera Pose Estimation. CVPRW, 2024.

Why simulation in robot learning?

- Quick prototyping
- Safer, can break things
- Cheaper data collection, testing
- Parallelise data collection and model training
- More control over environment, no random data
- Ground truthing is easy
- There is no choice – no data from operating environment until deployment

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Imitation learning

- *"The study of algorithms that improve decision making through data collected by observing an expert who can accomplish a task that is hard to hand-program."*
- The expert is not necessarily a human (e.g., simulation engine).

J. Andrew (Drew) Bagnell. An Invitation to Imitation. Tech. Report, CMU-RI-TR-15-08, Robotics Institute, Carnegie Mellon University, March, 2015

Human expert demonstration to train a walking robot to cross very rough terrain.

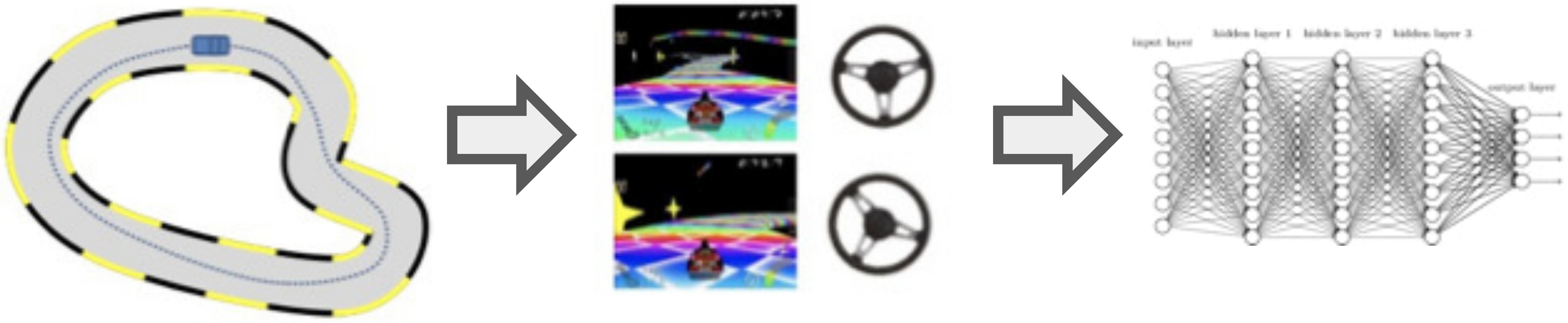
M. Zucker, N. Ratliff, M. Stolle, J. Chestnutt, J Andrew Bagnell, C. G. Atkeson, and J. Kuffner. Optimization and learning for rough terrain legged locomotion. The International Journal of Robotics Research, 30(2):175–191, 2011.

Imitation Learning in a Nutshell

Given: demonstrations or demonstrator

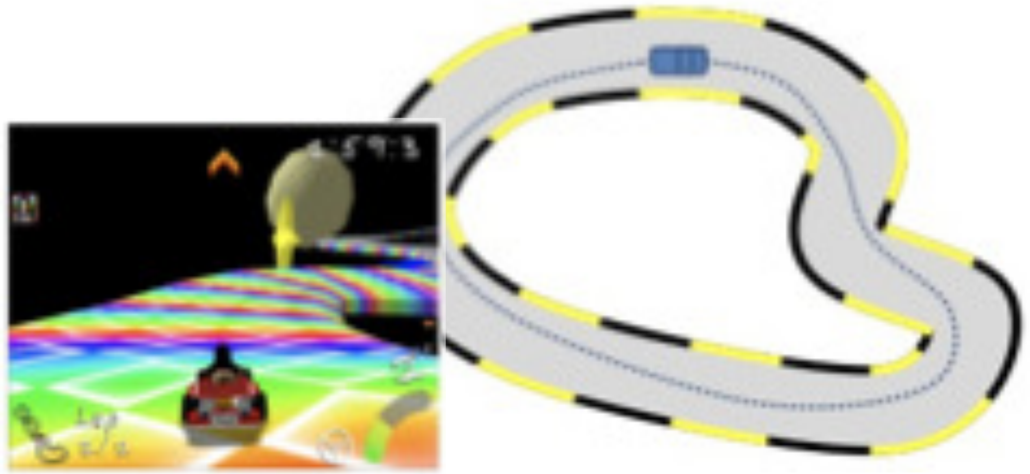
Goal: train a policy to mimic demonstrations

Expert Demonstrations — State/Action Pairs — Learning

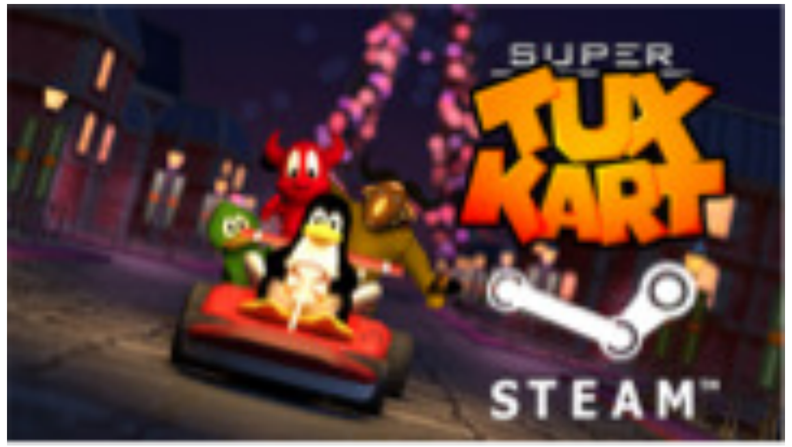


Images from Stephane Ross

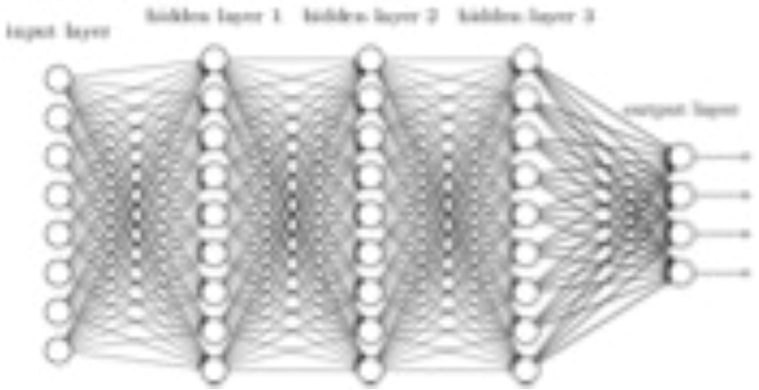
Ingredients of Imitation Learning



Demonstrations or Demonstrator



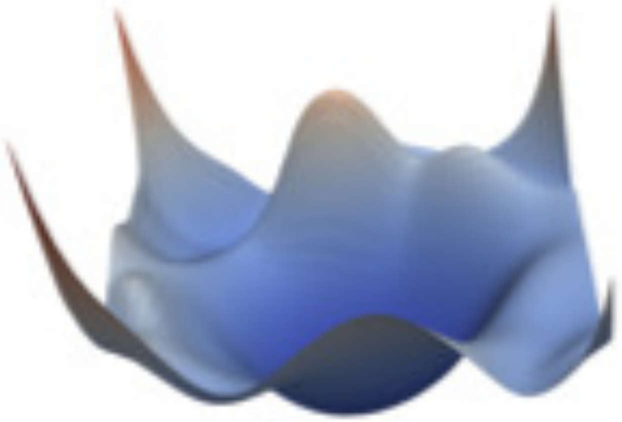
Environment / Simulator



Policy Class

vs

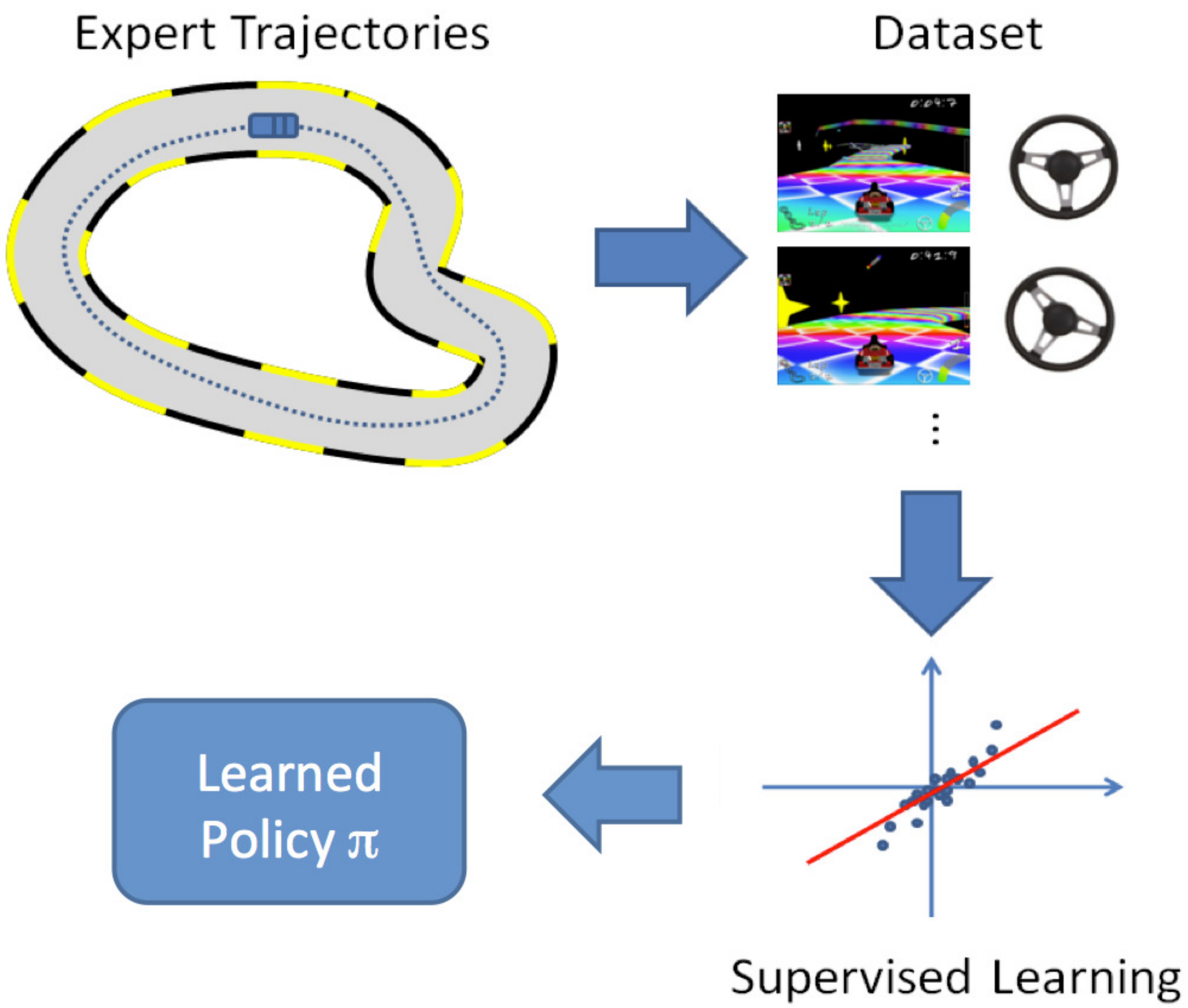
Loss Function



Learning Algorithm

Page from Yisong Yue and Hoang Minh Le, Imitation Learning Tutorial, ICML 2018.

Behavioural cloning



- Supervised learning to learn a <u>policy</u> that predicts steering angle for each input image.
- Here, a policy is a learned predictor that maps inputs to actions.
- Train the policy model based on

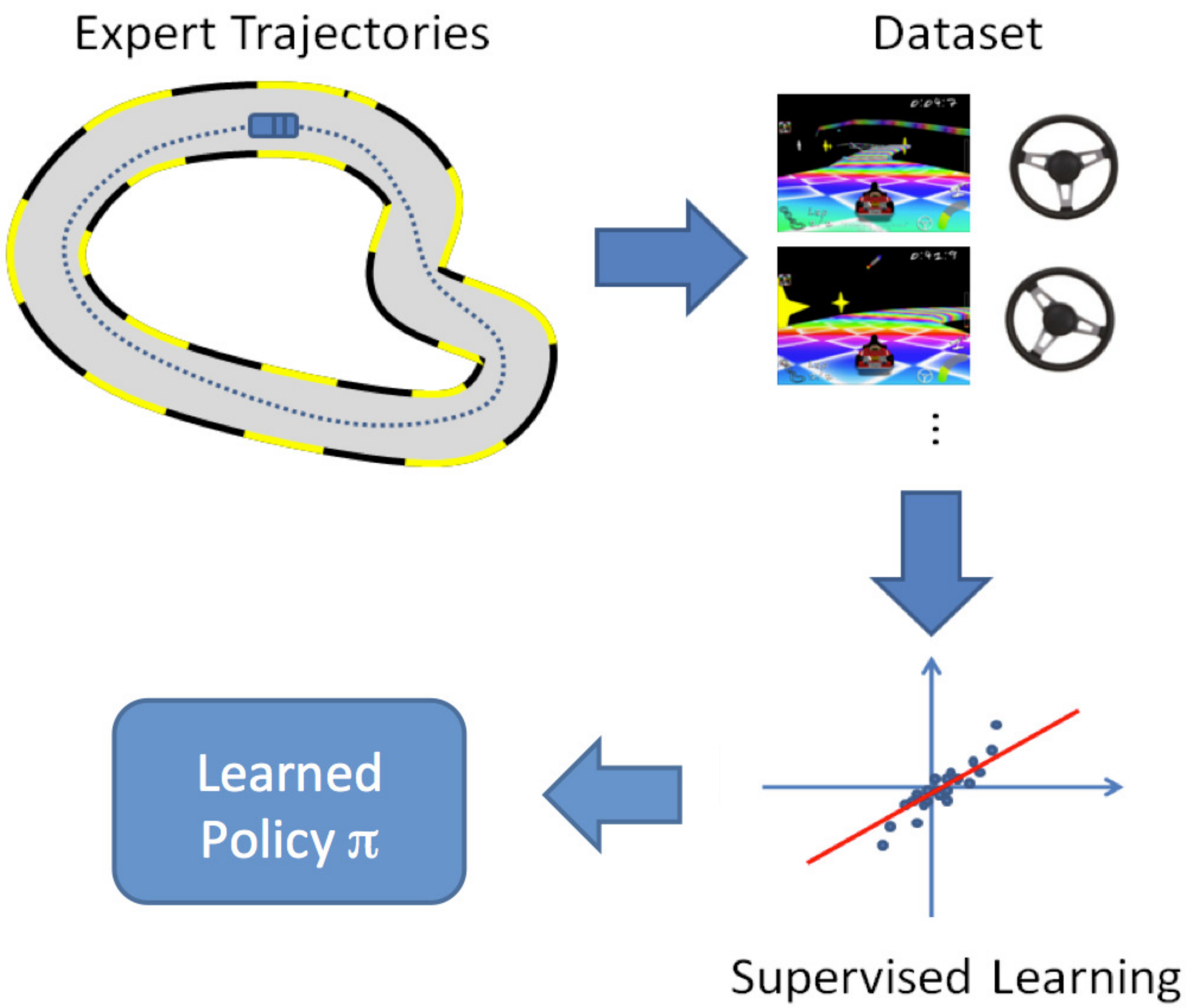
<image, steering angle>

pairs collected from from past histories of driving by an expert.

Can the car drive itself?

J. Andrew (Drew) Bagnell. An Invitation to Imitation. Tech. Report, CMU-RI-TR-15-08, Robotics Institute, Carnegie Mellon University, March, 2015

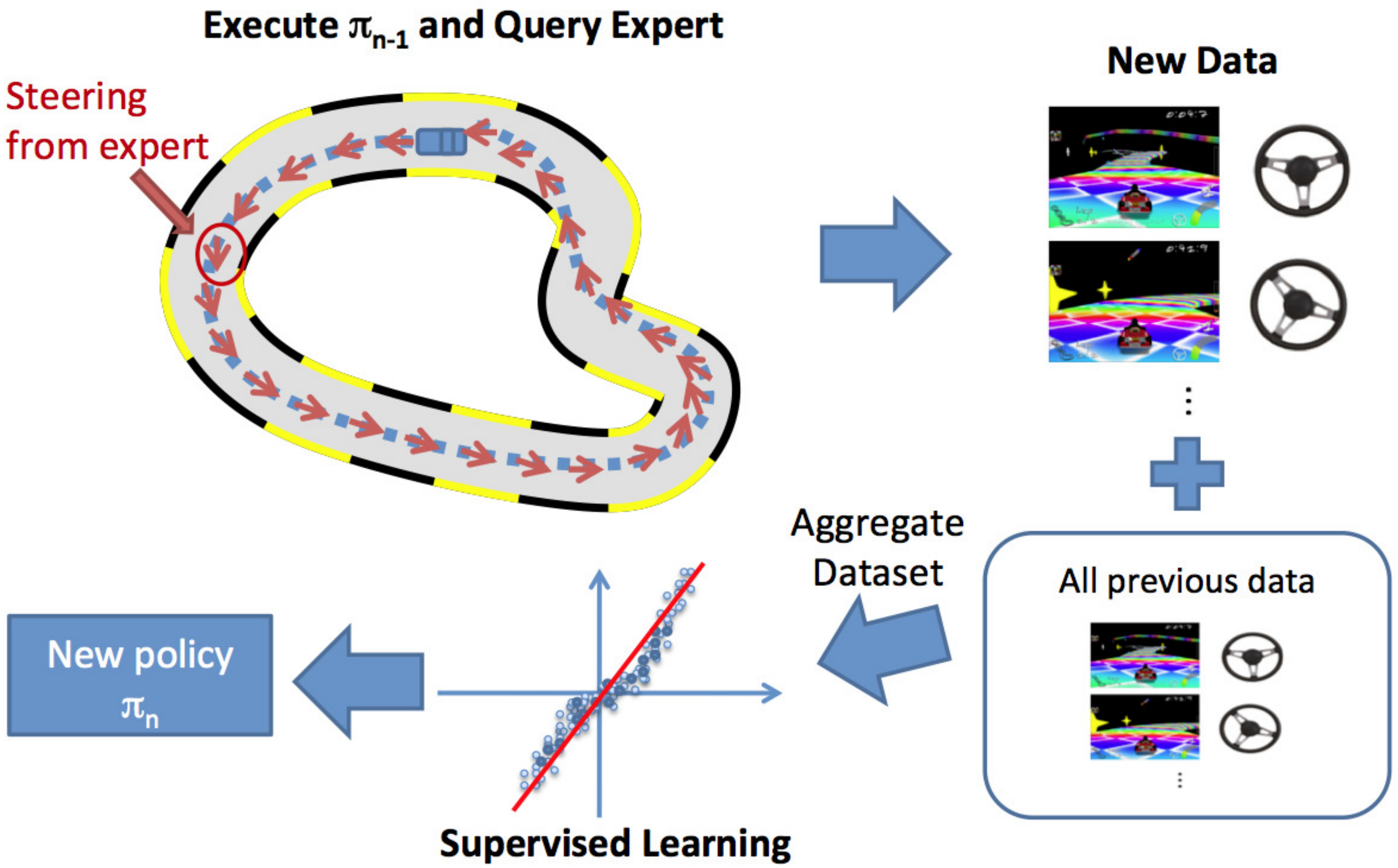
Behavioural cloning



- Does not work due to error build-up---the agent is unable to recover from mistakes.
- Fundamentally, the data encountered during driving is not i.i.d., i.e., a basic assumption of supervised learning is violated.
- *"One cannot learn to drive a car simply by watching someone else do it."*

J. Andrew (Drew) Bagnell. An Invitation to Imitation. Tech. Report, CMU-RI-TR-15-08, Robotics Institute, Carnegie Mellon University, March, 2015

Data Aggregation (DAGGer)



J. Andrew (Drew) Bagnell. An Invitation to Imitation. Tech. Report, CMU-RI-TR-15-08, Robotics Institute, Carnegie Mellon University, March, 2015

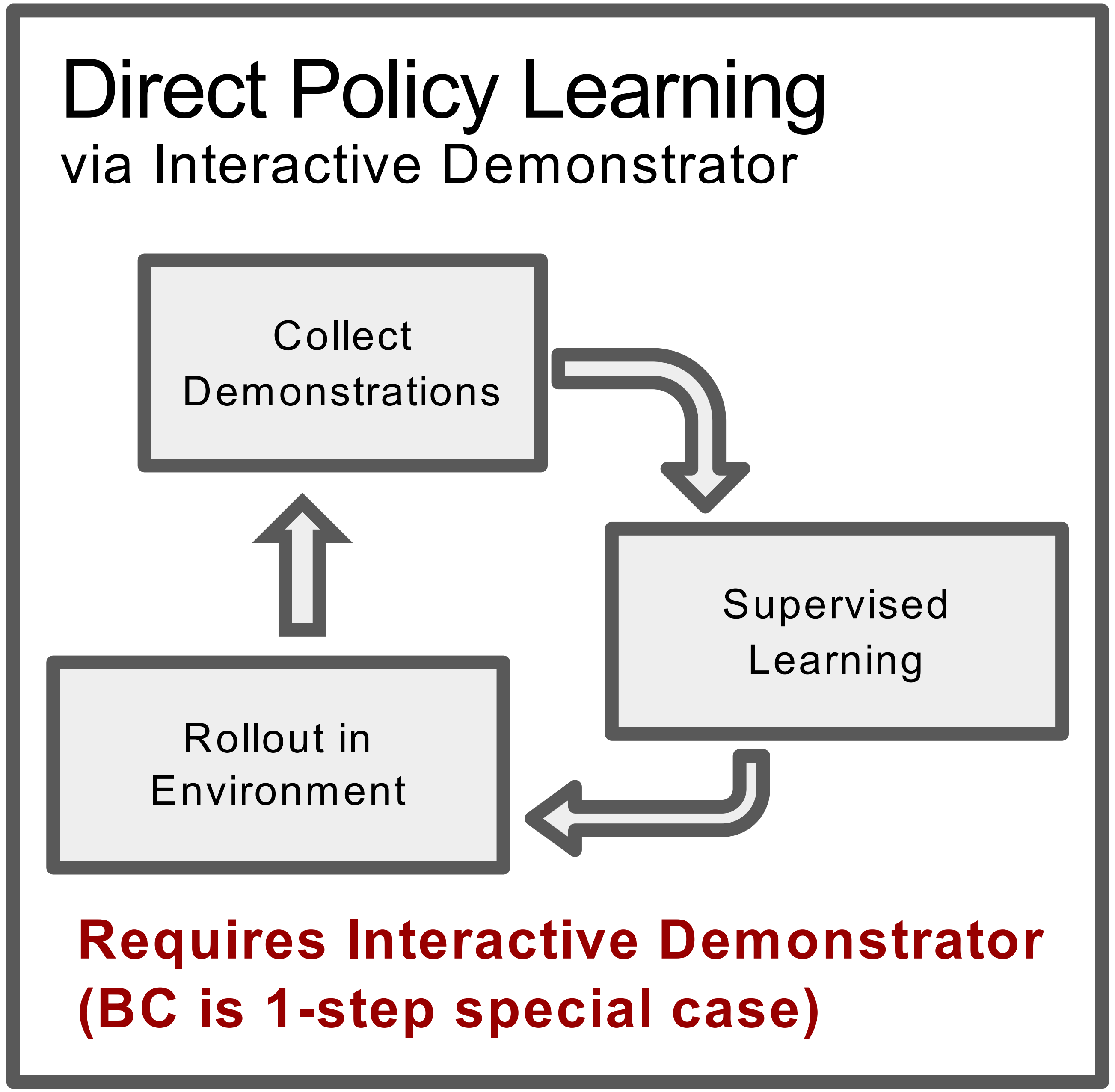


Diagram from Yisong Yue and Hoang Minh Le, Imitation Learning Tutorial, ICML 2018.

ALVINN: An Autonomous Land Vehicle in a Neural Network (1989)

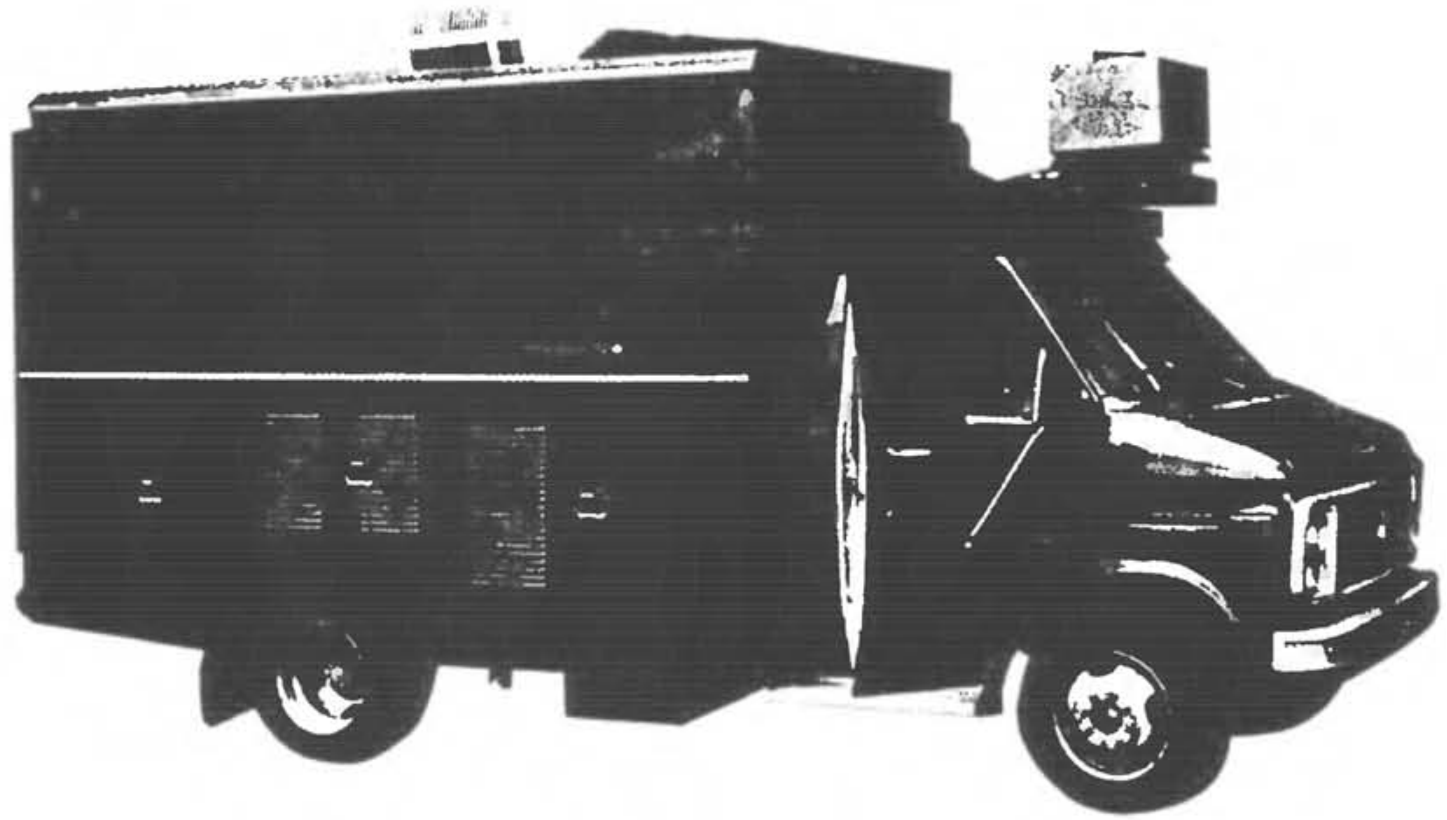


Figure 3: NAVLAB, the CMU autonomous navigation test vehicle.

J. Andrew (Drew) Bagnell. An Invitation to Imitation. Tech. Report, CMU-RI-TR-15-08, Robotics Institute, Carnegie Mellon University, March, 2015

D. Pomerleau. ALVINN: An Autonomous Land Vehicle in a Neural Network. In Advances in Neural Information Processing Systems (NIPS), 1989.

ALVINN: An Autonomous Land Vehicle in a Neural Network (1989)

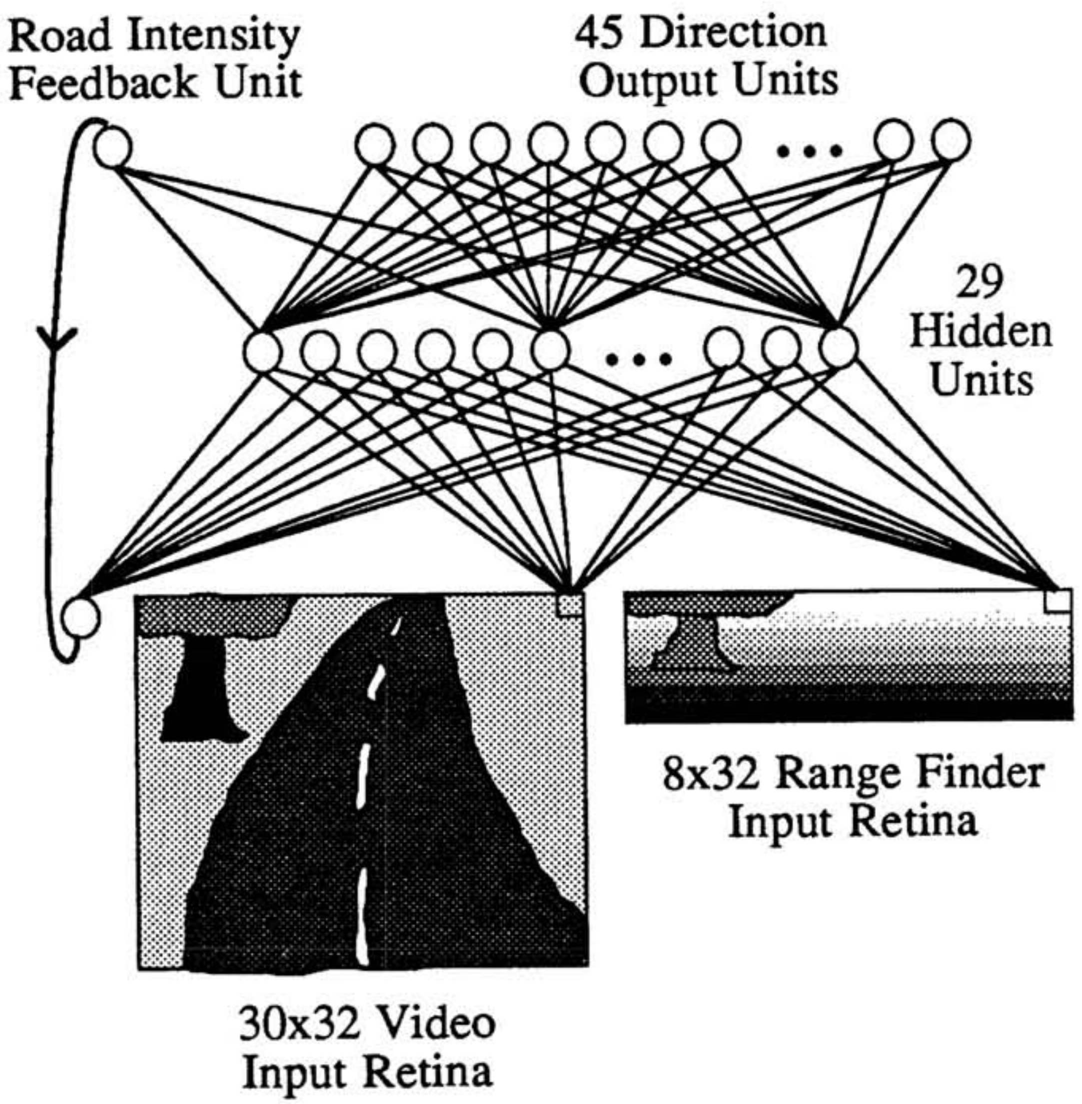


Figure 1: ALVINN Architecture

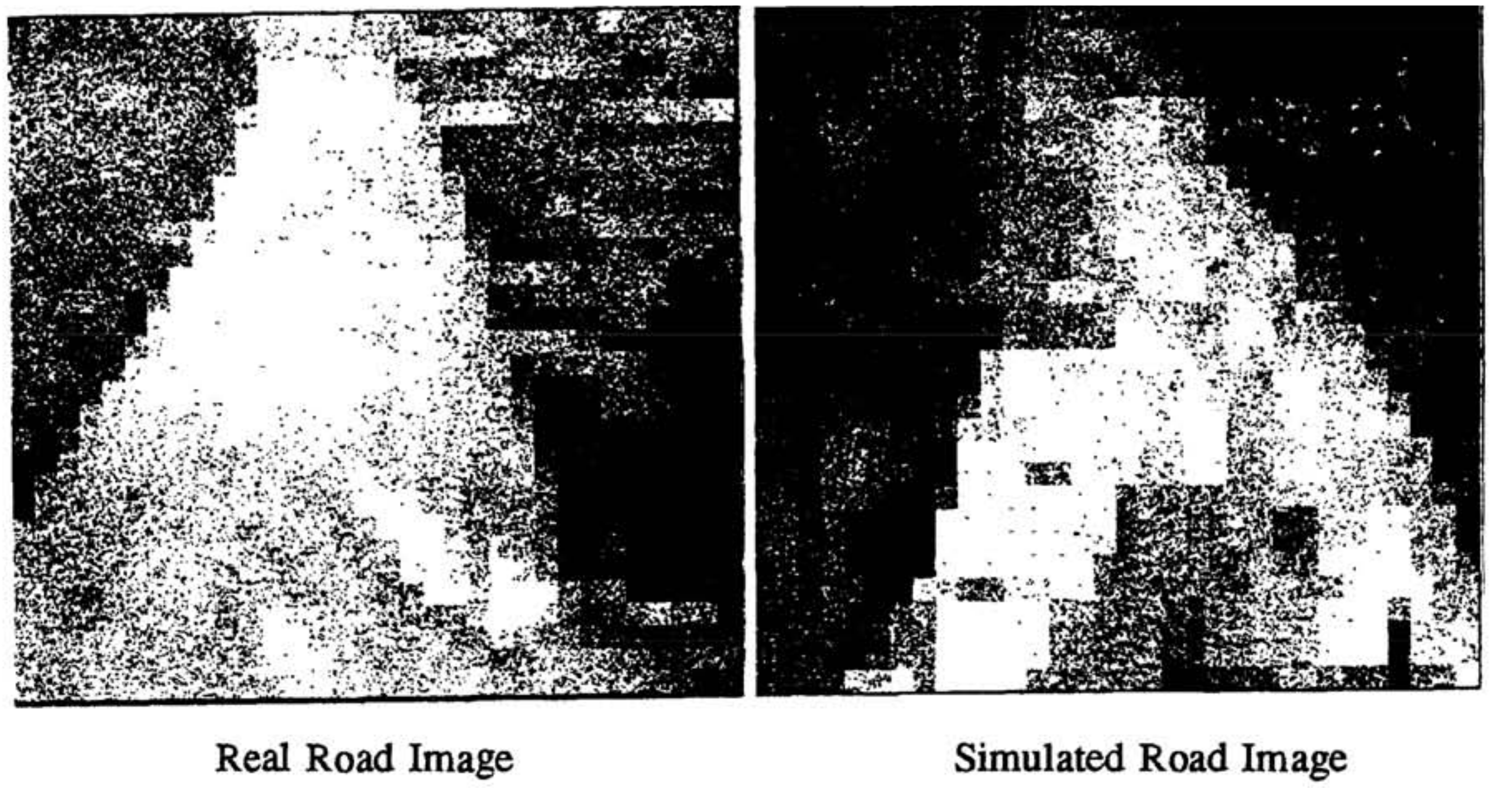


Figure 2: Real and simulated road images

TRAINING AND PERFORMANCE

Training on actual road images is logistically difficult, because in order to develop a general representation, the network must be presented with a large number of training exemplars depicting roads under a wide variety of conditions. Collection of such a data set would be difficult, and changes in parameters such as camera orientation would require collecting an entirely new set of road images. To avoid these difficulties we have developed a simulated road generator which creates road images to be used as training exemplars for the network. Figure 2 depicts the video images of one real and one artificial road. Although not shown in Figure 2, the road generator also creates corresponding simulated range finder images. At the relatively low resolution being used it is difficult to distinguish between real and simulated roads.

D. Pomerleau. ALVINN: An Autonomous Land Vehicle in a Neural Network. In Advances in Neural Information Processing Systems (NIPS), 1989.

ALVINN: An Autonomous Land Vehicle in a Neural Network (1989)

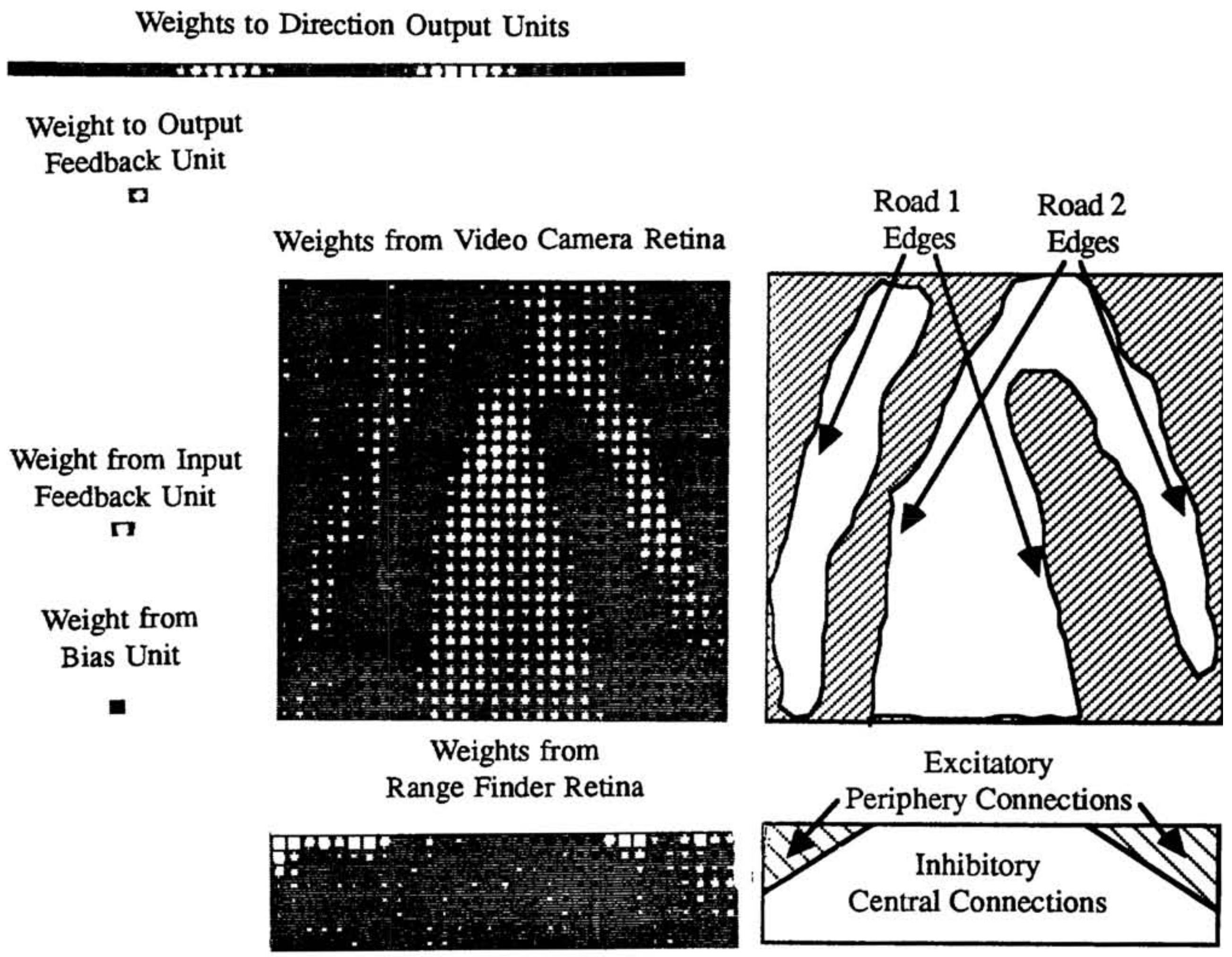


Figure 4: Diagram of weights projecting to and from a typical hidden unit in a network trained on roads with a fixed width. The schematics on the right are aids for interpretation.

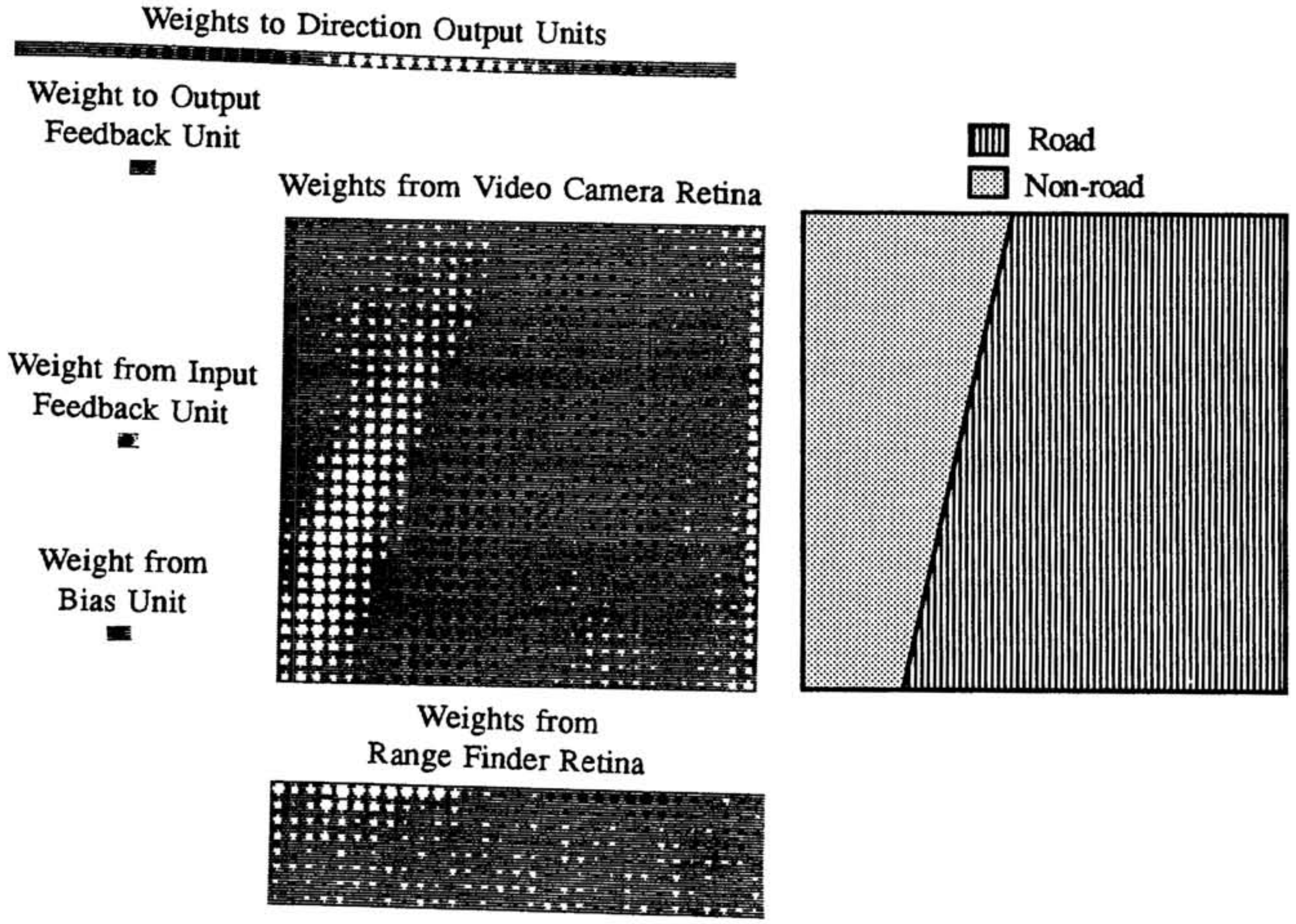


Figure 5: Diagram of weights projecting to and from a typical hidden unit in a network trained on roads with different widths.

D. Pomerleau. ALVINN: An Autonomous Land Vehicle in a Neural Network. In Advances in Neural Information Processing Systems (NIPS), 1989.

End to End Learning for Self-Driving Cars (2016)

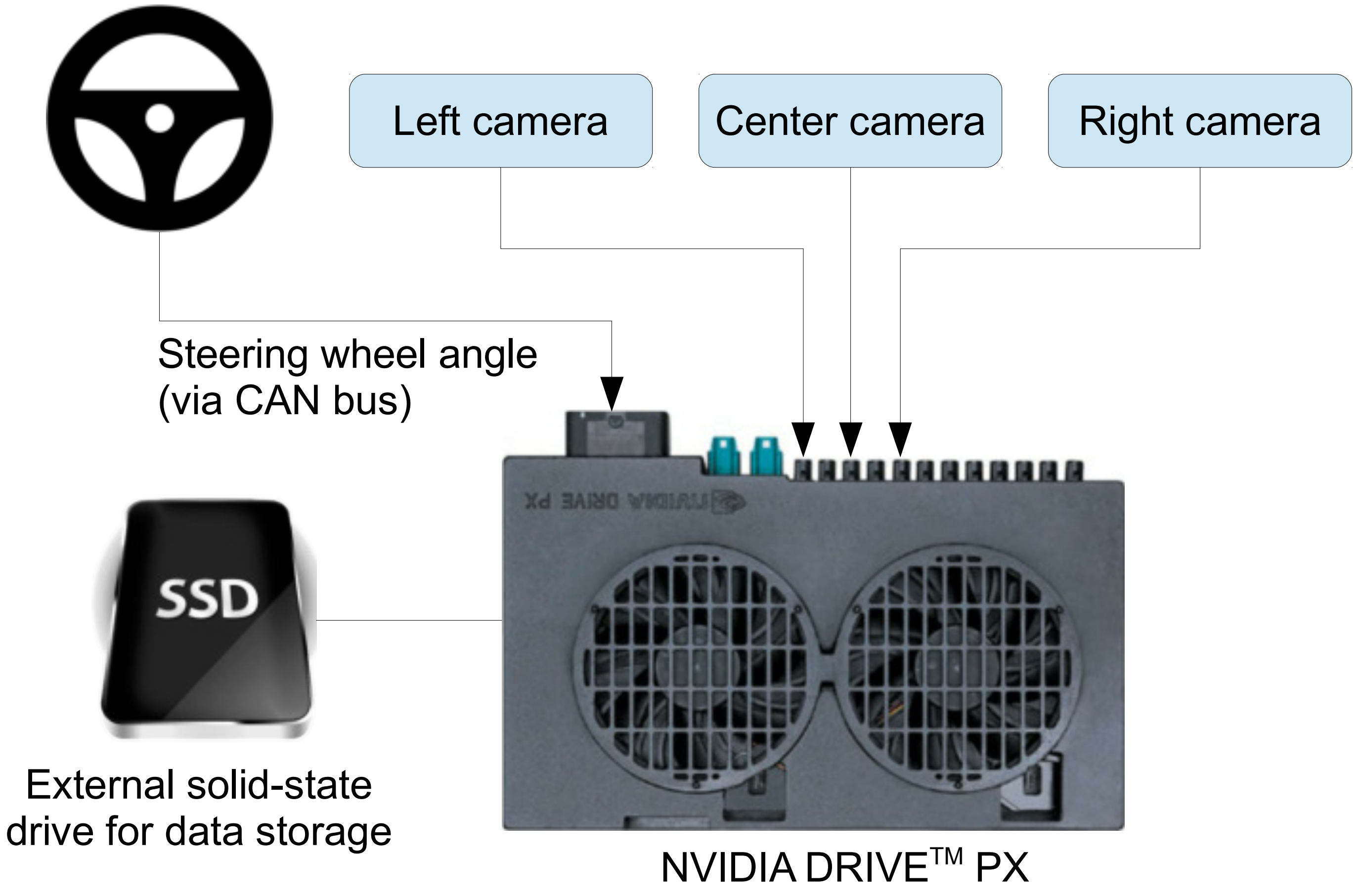


Figure 1: High-level view of the data collection system.

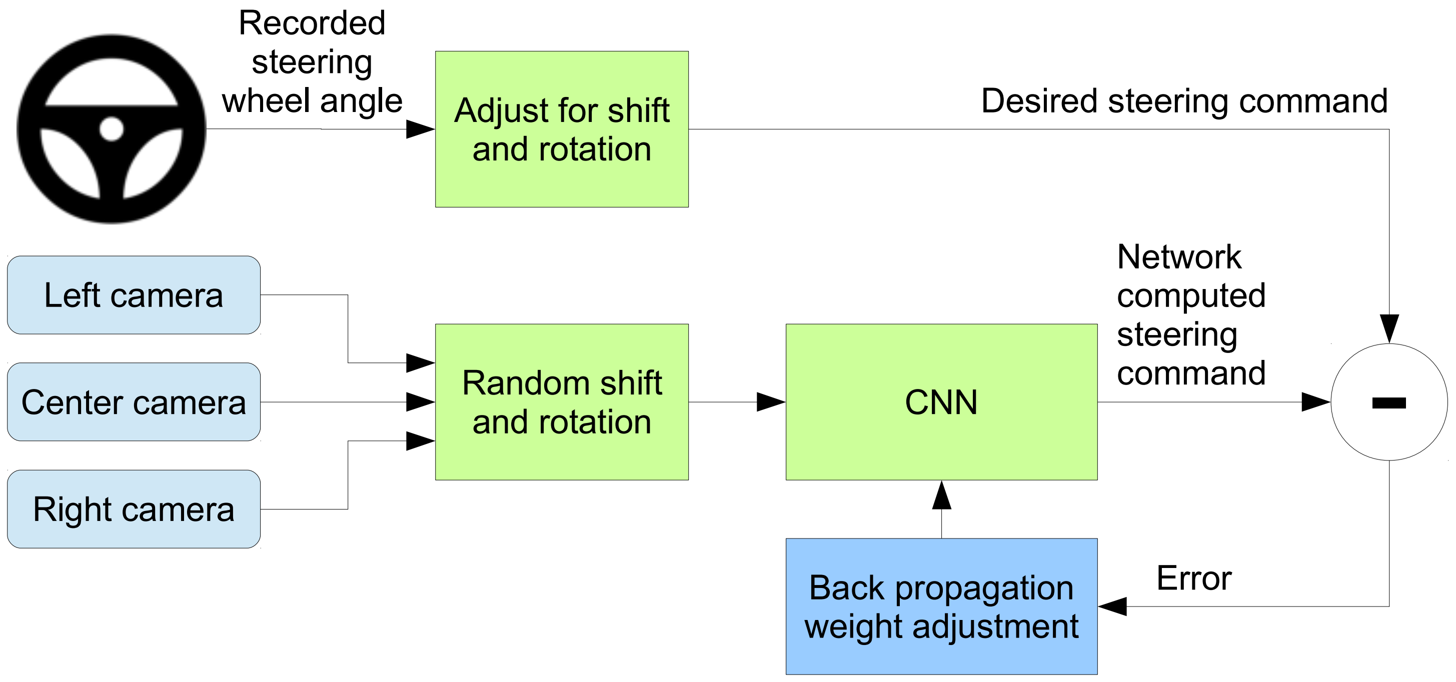


Figure 2: Training the neural network.

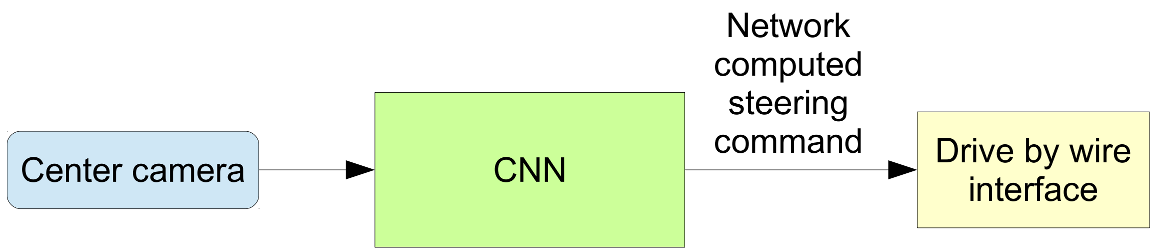


Figure 3: The trained network is used to generate steering commands from a single front-facing center camera.

M. Bojarski, D. D. Testa, D. Dworakowski, B. Firner, B. Flepp, P. Goyal, L. D. Jackel, et al. End to end learning for self-driving cars. arXiv:1604.07316, 2016.

End to End Learning for Self-Driving Cars (2016)

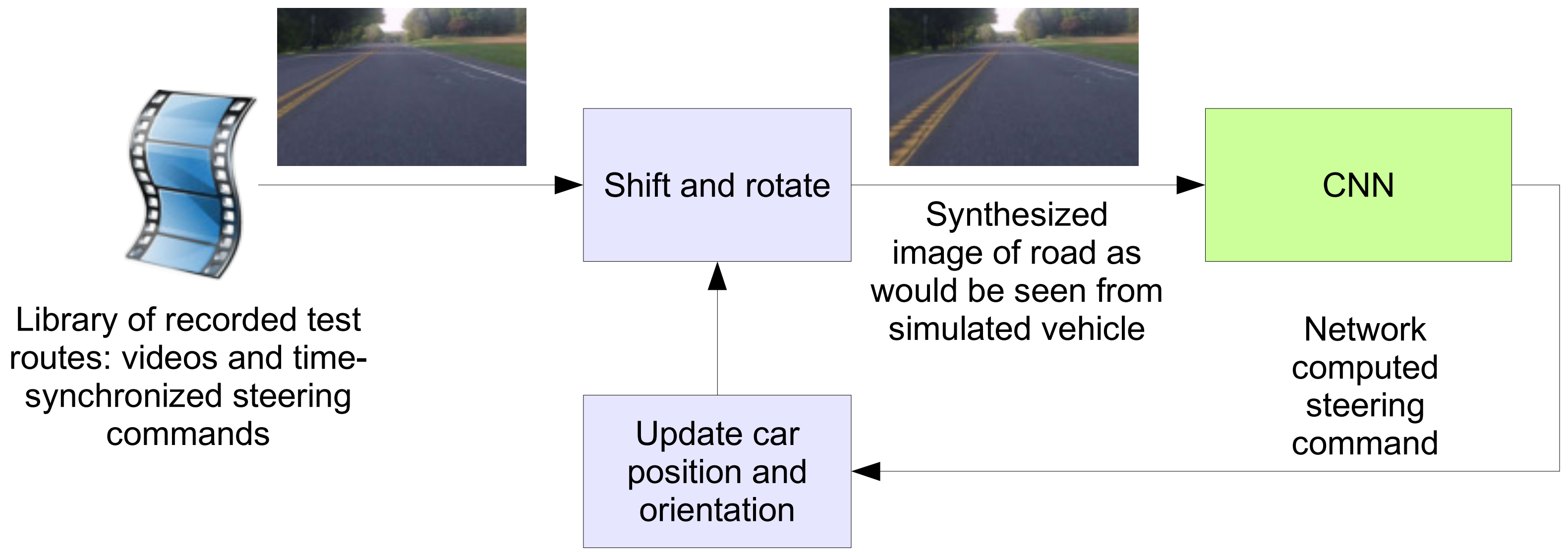


Figure 5: Block-diagram of the drive simulator.

Figure 6: Screen shot of the simulator in interactive mode. See Section 7.1 for explanation of the performance metrics. The green area on the left is unknown because of the viewpoint transformation. The highlighted wide rectangle below the horizon is the area which is sent to the CNN.

M. Bojarski, D. D. Testa, D. Dworakowski, B. Firner, B. Flepp, P. Goyal, L. D. Jackel, et al. End to end learning for self-driving cars. arXiv:1604.07316, 2016.

End to End Learning for Self-Driving Cars (2016)

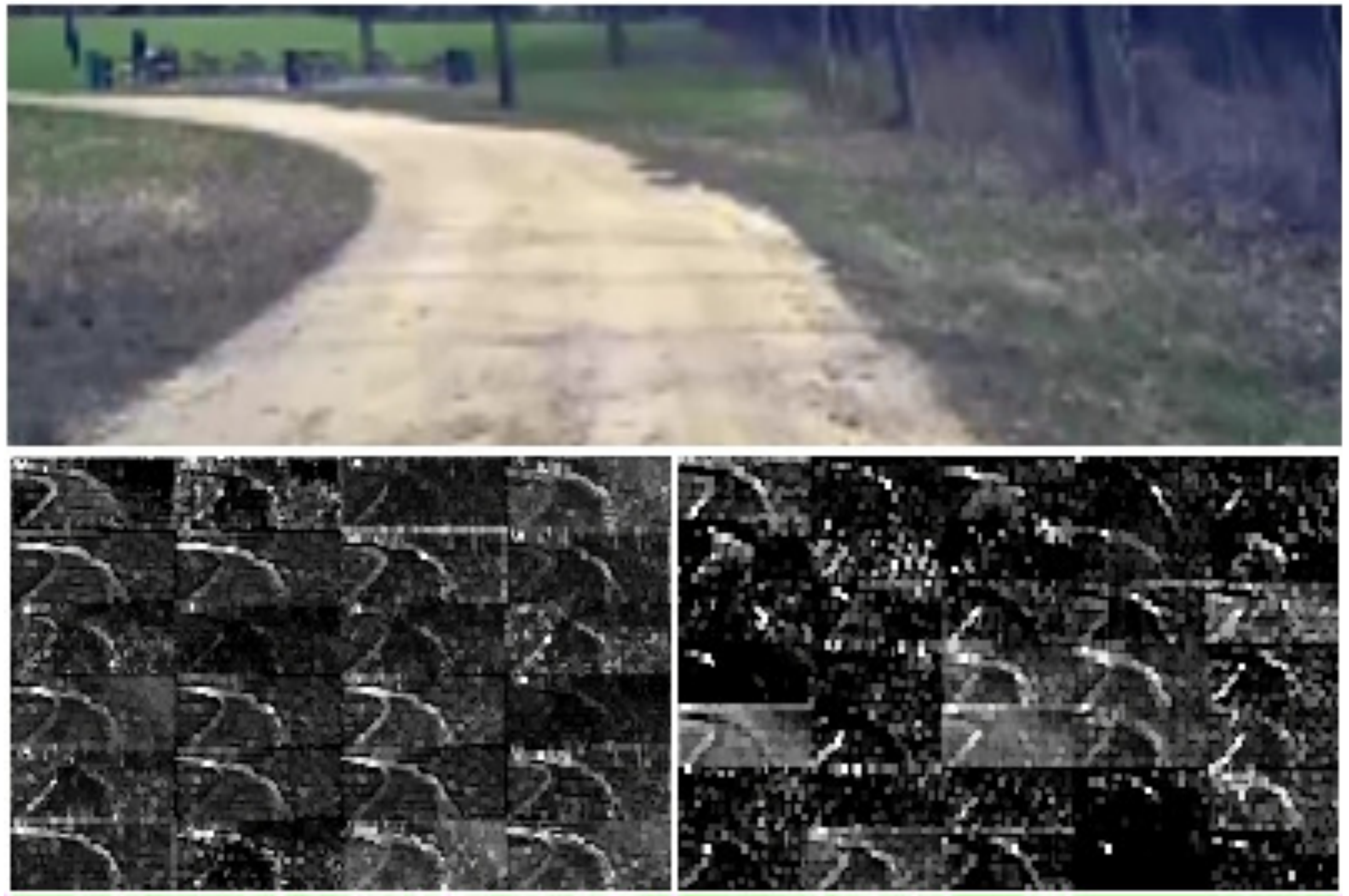


Figure 7: How the CNN "sees" an unpaved road. Top: subset of the camera image sent to the CNN. Bottom left: Activation of the first layer feature maps. Bottom right: Activation of the second layer feature maps. This demonstrates that the CNN learned to detect useful road features on its own, i. e., with only the human steering angle as training signal. We never explicitly trained it to detect the outlines of roads.

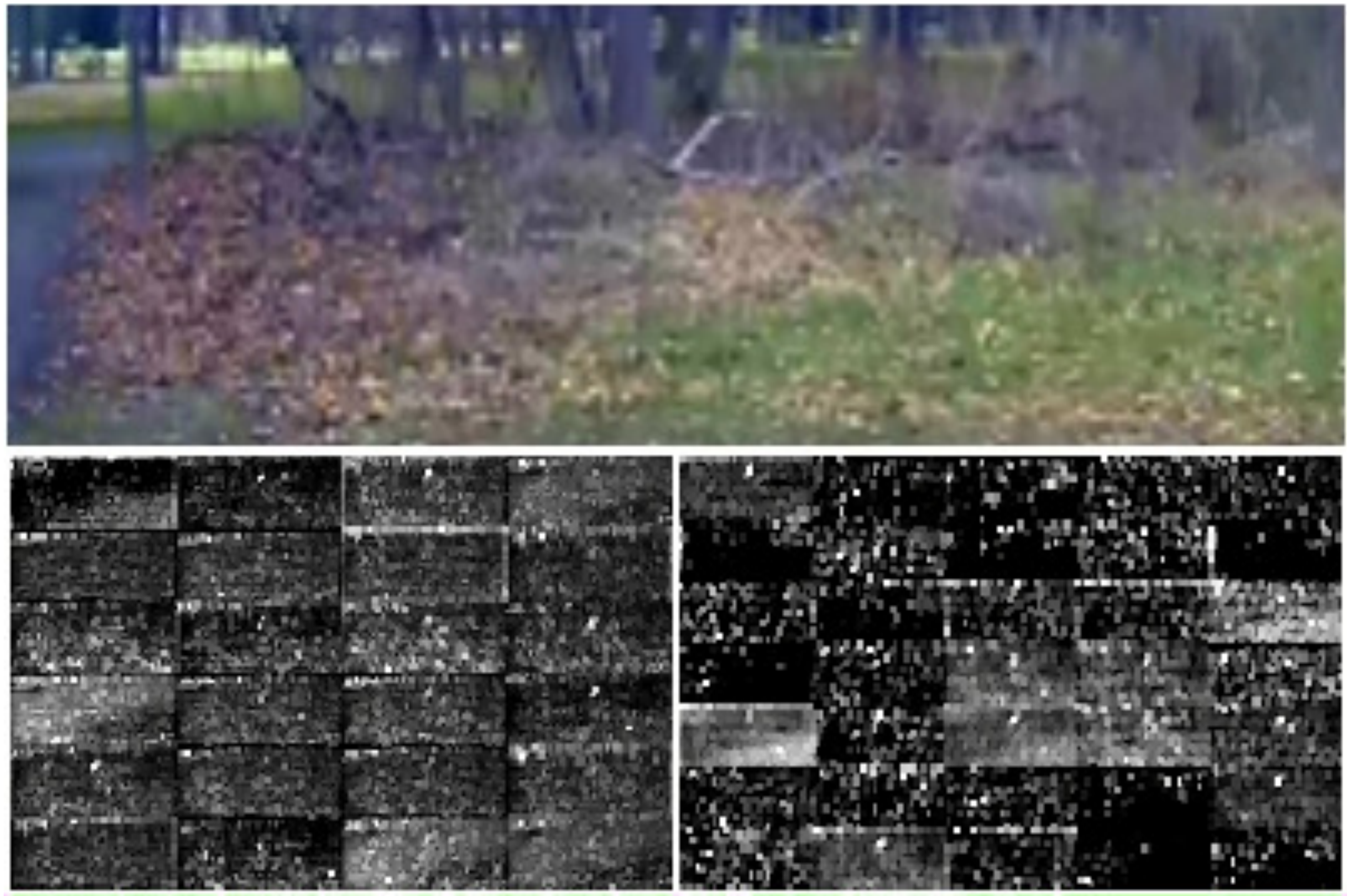


Figure 8: Example image with no road. The activations of the first two feature maps appear to contain mostly noise, i. e., the CNN doesn't recognize any useful features in this image.

M. Bojarski, D. D. Testa, D. Dworakowski, B. Firner, B. Flepp, P. Goyal, L. D. Jackel, et al. End to end learning for self-driving cars. arXiv:1604.07316, 2016.

End-to-end Driving via Conditional Imitation Learning (2018)

Ambiguity at junctions – the correct steering angle depends on higher-level intentions.

(a) Aerial view of test environment (b) Vision-based driving, view from onboard camera (c) Side view of vehicle

Fig. 1. Conditional imitation learning allows an autonomous vehicle trained end-to-end to be directed by high-level commands. (a) We train and evaluate robotic vehicles in the physical world (top) and in simulated urban environments (bottom). (b) The vehicles drive based on video from a forward-facing onboard camera. At the time these images were taken, the vehicle was given the command "turn right at the next intersection". (c) The trained controller handles sensorimotor coordination (staying on the road, avoiding collisions) and follows the provided commands.

F. Codevilla, M. Mu¨ller, A. Dosovitskiy, A. Lo´pez, and V. Koltun. End-to-end driving via conditional imitation learning. In ICRA, 2018.

End-to-end Driving via Conditional Imitation Learning (2018)

F. Codevilla, M. Müller, A. Dosovitskiy, A. López, and V. Koltun. End-to-end driving via conditional imitation learning. In ICRA, 2018.

End-to-end Driving via Conditional Imitation Learning (2018)

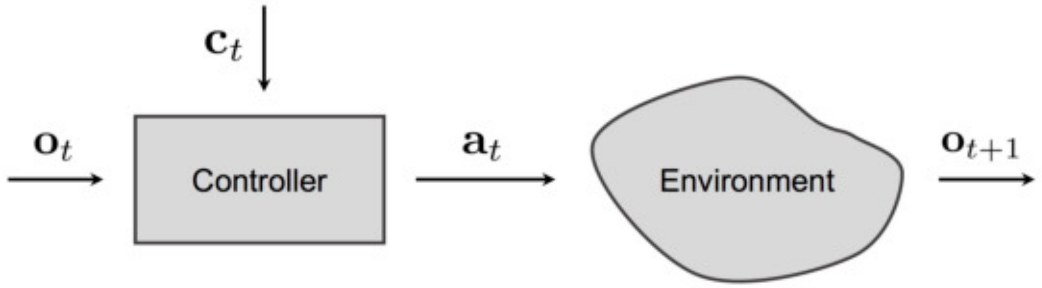
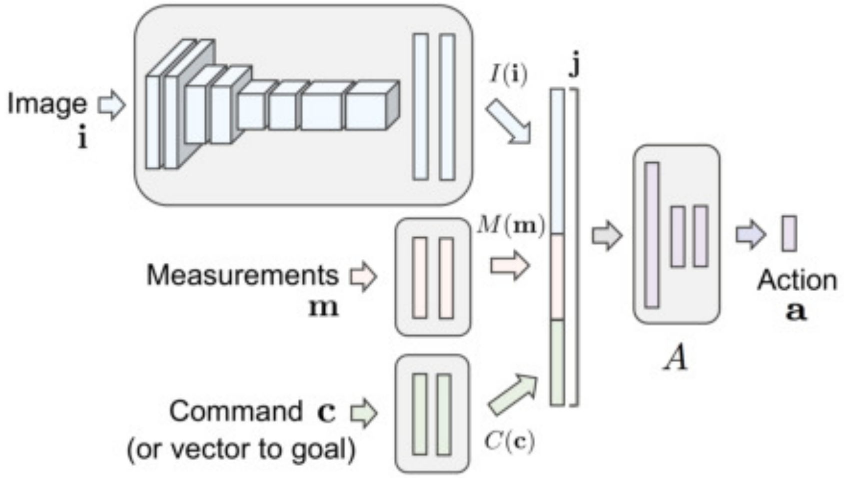
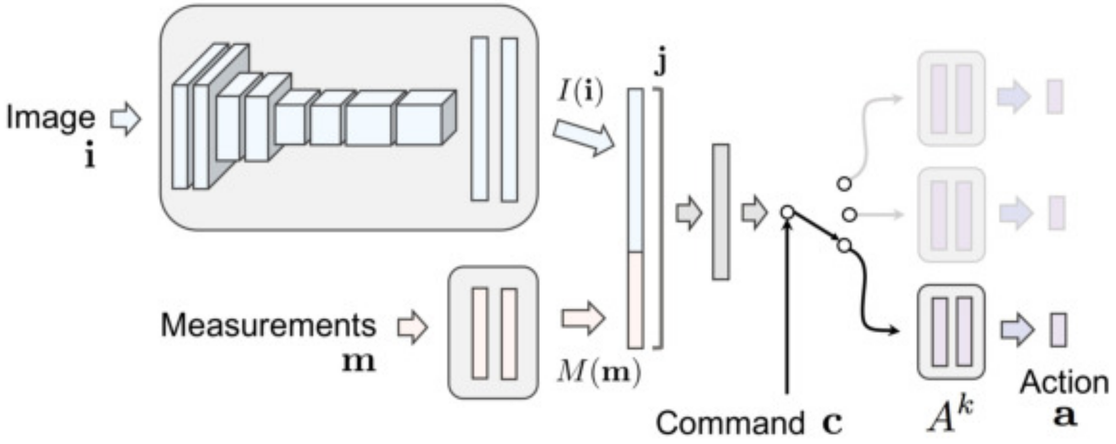


Fig. 2. High-level overview. The controller receives an observation $\mathbf{o}_t$ from the environment and a command $\mathbf{c}_t$. It produces an action $\mathbf{a}_t$ that affects the environment, advancing to the next time step.



(a)



(b)

Fig. 3. Two network architectures for command-conditional imitation learning. (a) `command input`: the command is processed as input by the network, together with the image and the measurements. The same architecture can be used for goal-conditional learning (one of the baselines in our experiments), by replacing the command by a vector pointing to the goal. (b) `branched`: the command acts as a switch that selects between specialized sub-modules.

F. Codevilla, M. Mu¨ller, A. Dosovitskiy, A. Lo´pez, and V. Koltun. End-to-end driving via conditional imitation learning. In ICRA, 2018.

Many other application areas

Robot manipulation

Fig. 1: Virtual Reality teleoperation in action

T. Zhang et al., "Deep Imitation Learning for Complex Manipulation Tasks from Virtual Reality Teleoperation," ICRA 2018.

Robot locomotion

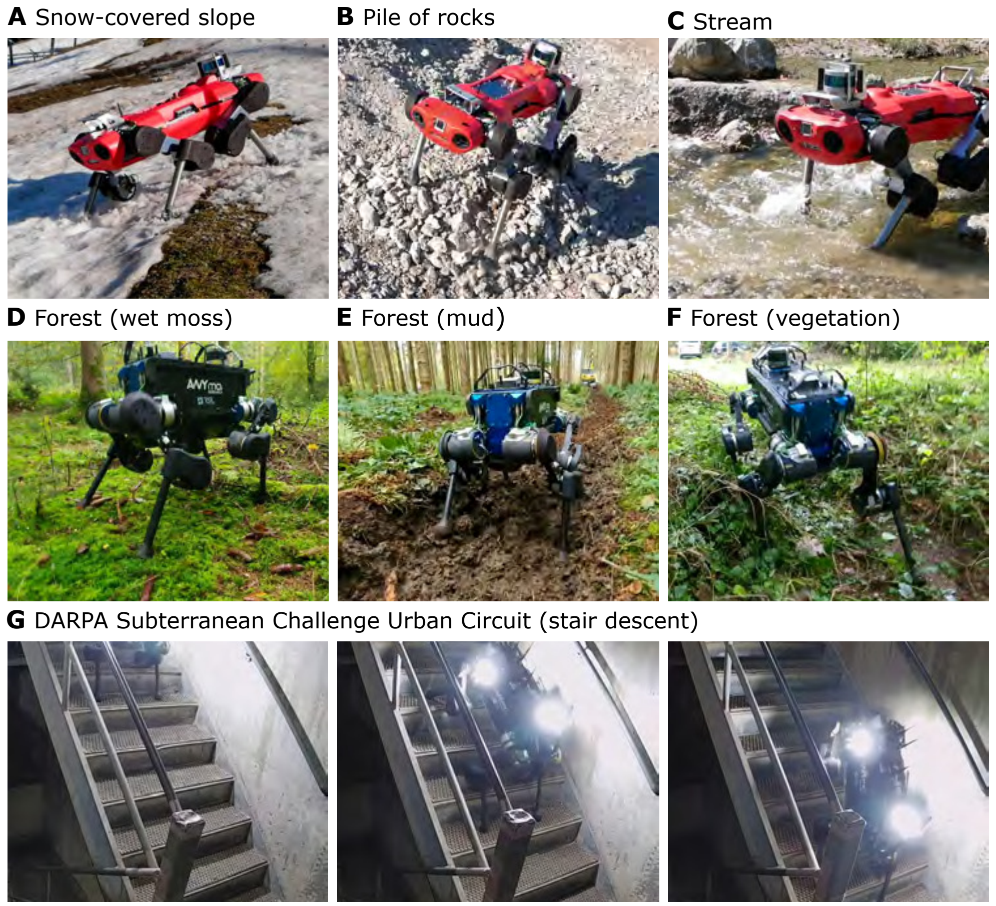
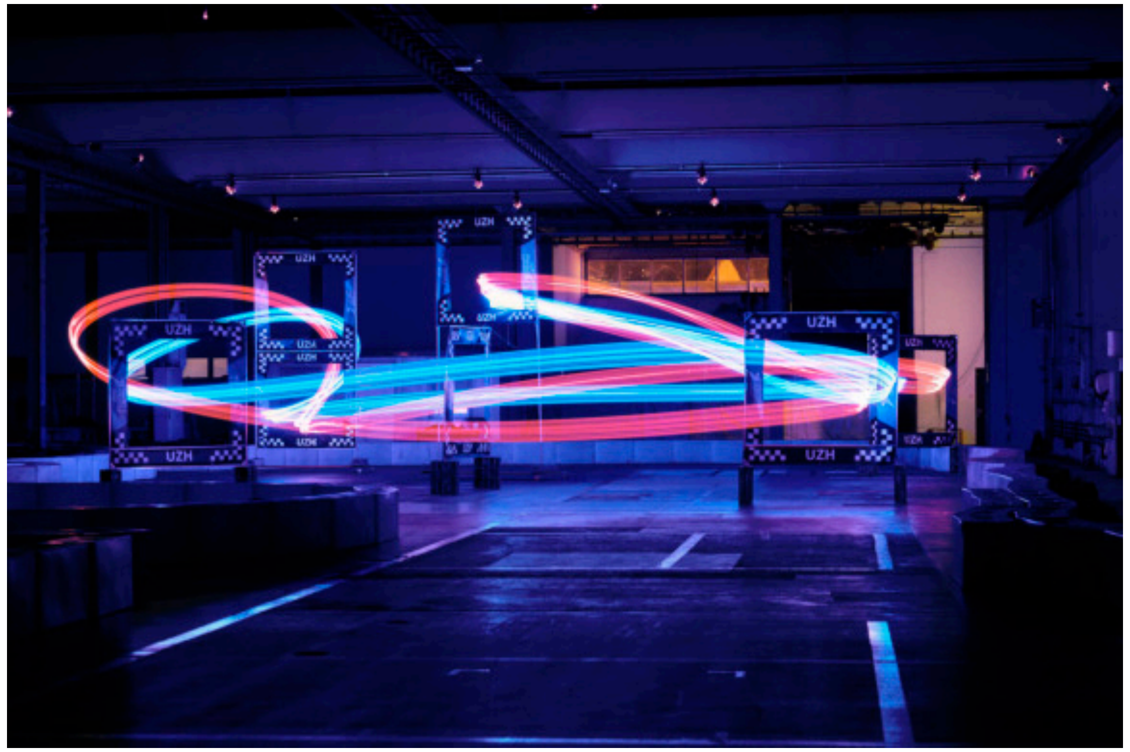


Fig. 2. A number of specific deployments. (**A-F**) Zero-shot generalization to slippery and deforming terrain. (**G**) Steep descent during the DARPA Subterranean Challenge. The stair rise is 18 cm and the slope is $\sim 45°$.

Joonho Lee, Jemin Hwangbo, Lorenz Wellhausen, Vladlen Koltun, and Marco Hutter. Learning Quadrupedal Locomotion over Challenging Terrain. Science Robotics Vol.5 eabc5986 (2020)

Drone flying/racing



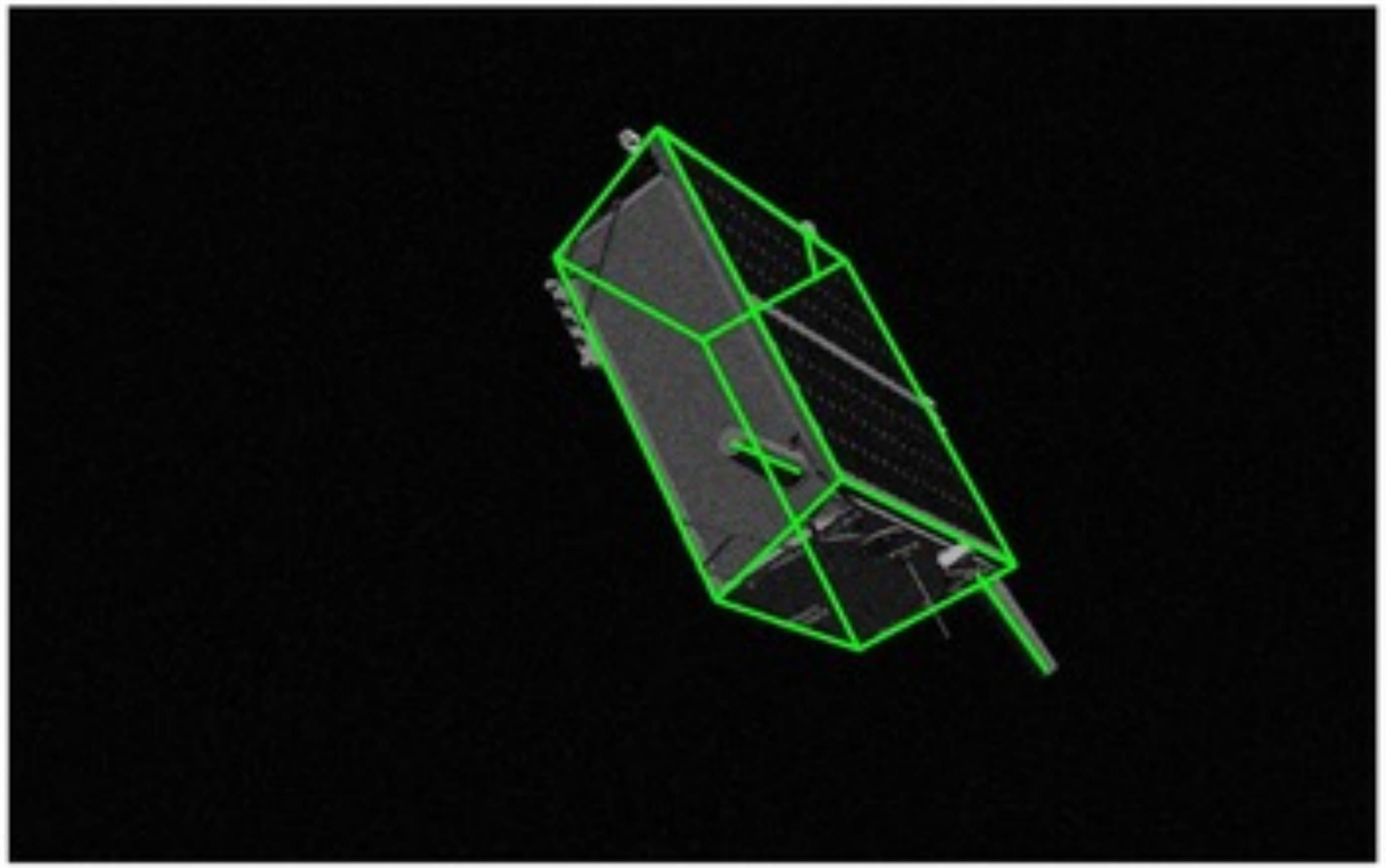
Jiaxu Xing, Angel Romero, Leonard Bauersfeld, Davide Scaramuzza. Bootstrapping Reinforcement Learning with Imitation for Vision-Based Agile Flight. arXiv, 2024.

Outline

- Track D: Robot Learning
- Motivation - why simulation in robot learning?
- Recap on imitation learning
- Recap on object pose estimation
- Popular simulators

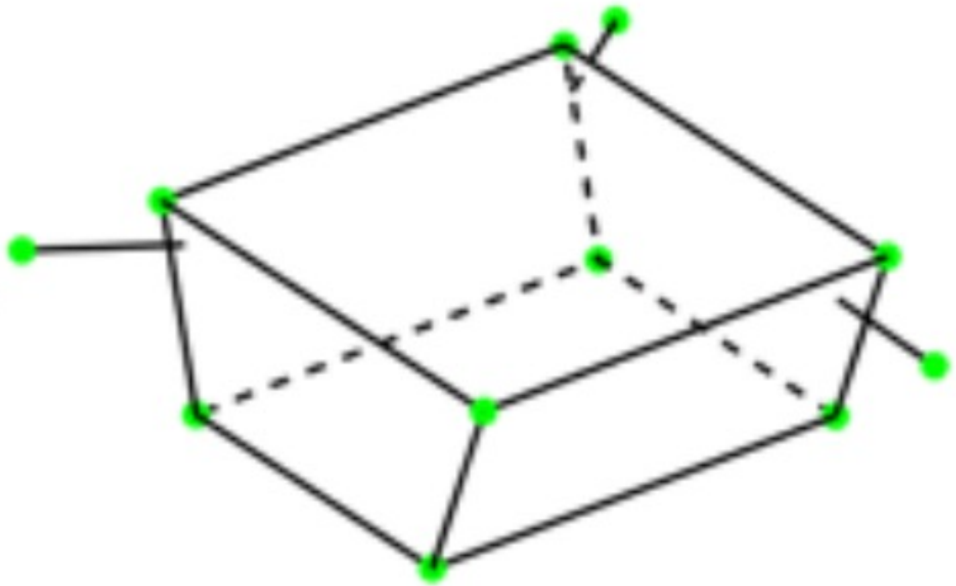
Spacecraft pose estimation – known target

Projection of 3D shape into image

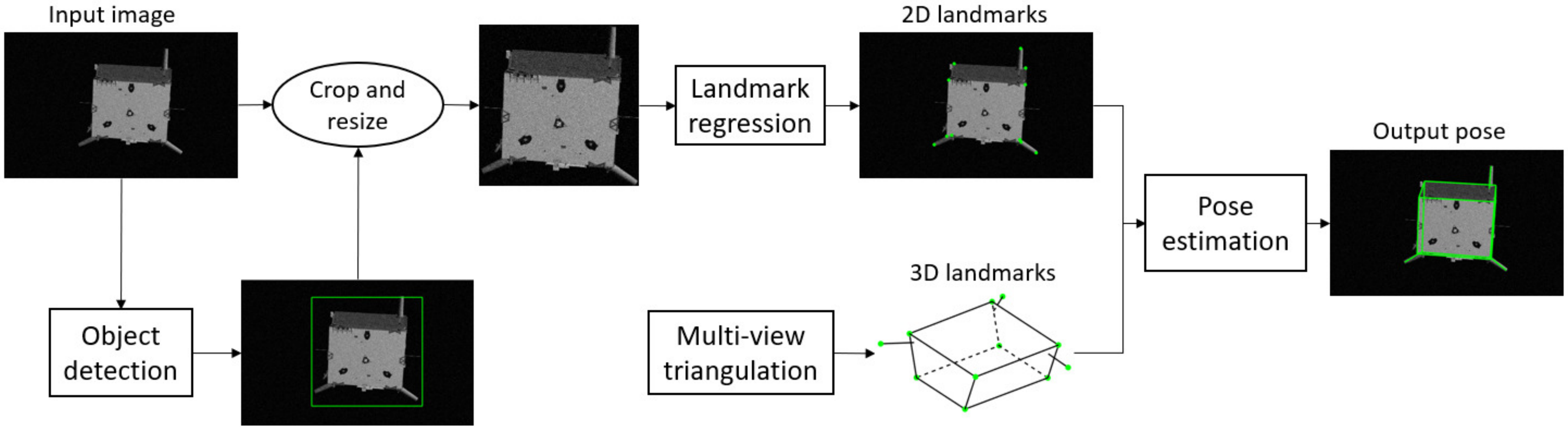


Estimate rigid body transformation

Known 3D structure



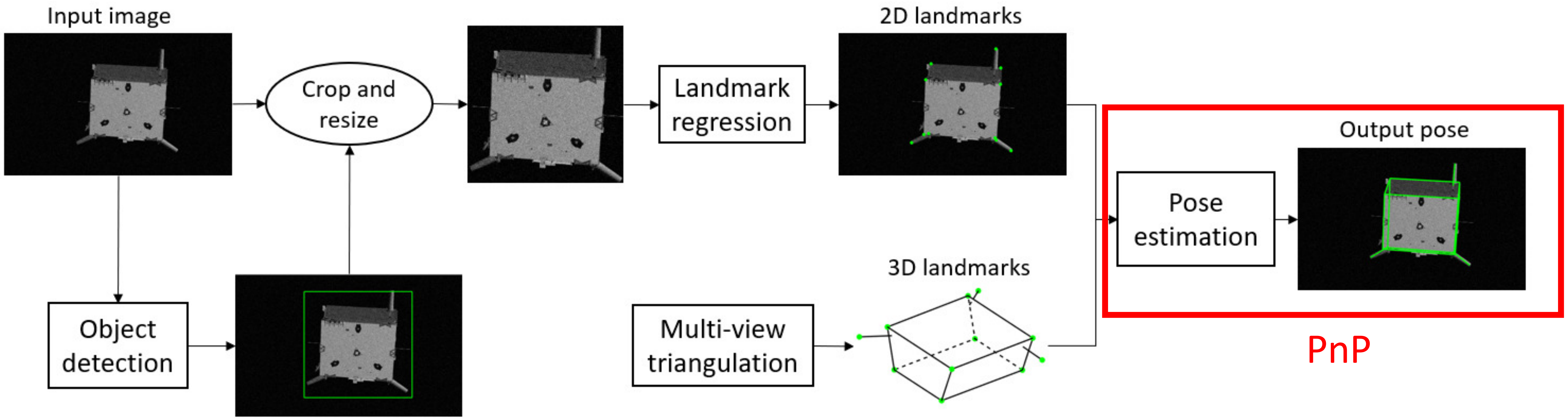
Pipeline



Pytorch implementation: https://github.com/BoChenYS/BPnP

B. Chen, J. Cao, A. Parra Bustos and T.-J. Chin. Satellite Pose Estimation with Deep Landmark Regression and Nonlinear Pose Refinement. ICCV 2019 Workshop on Recovering 6D Object Pose.

Pipeline



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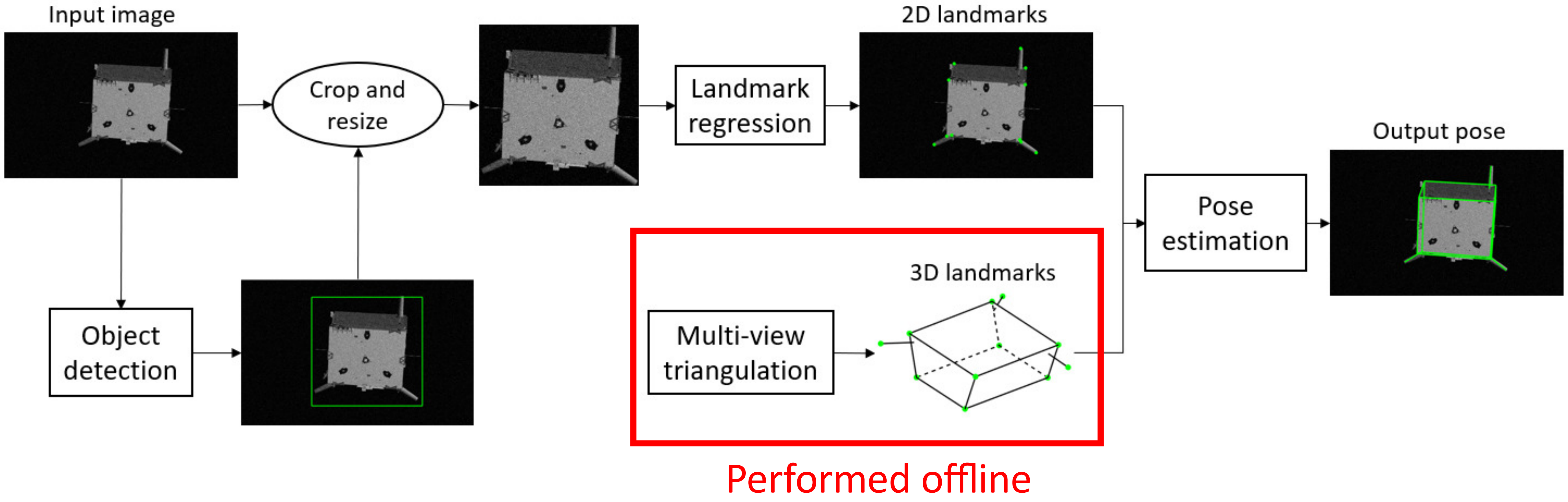

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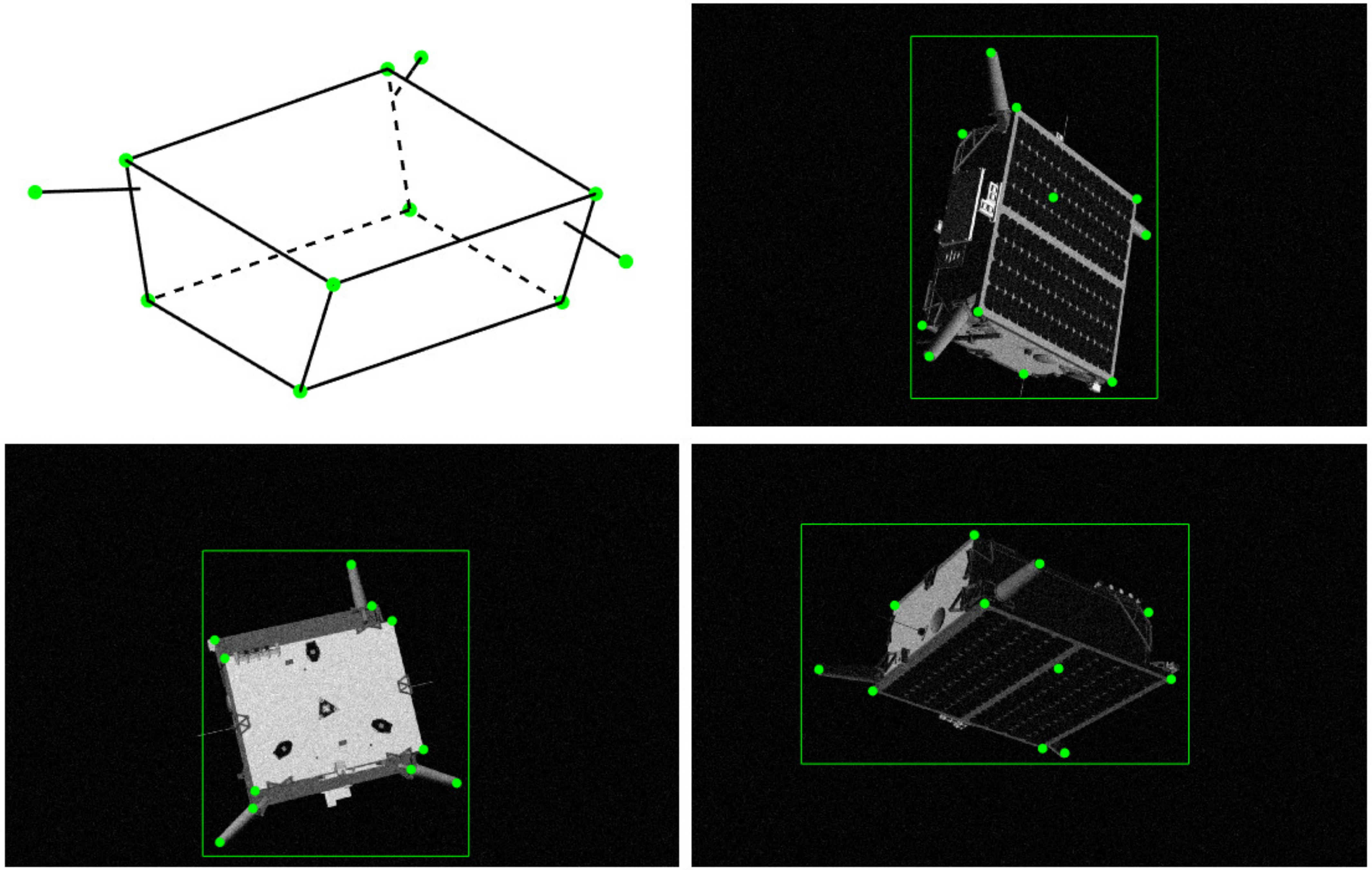
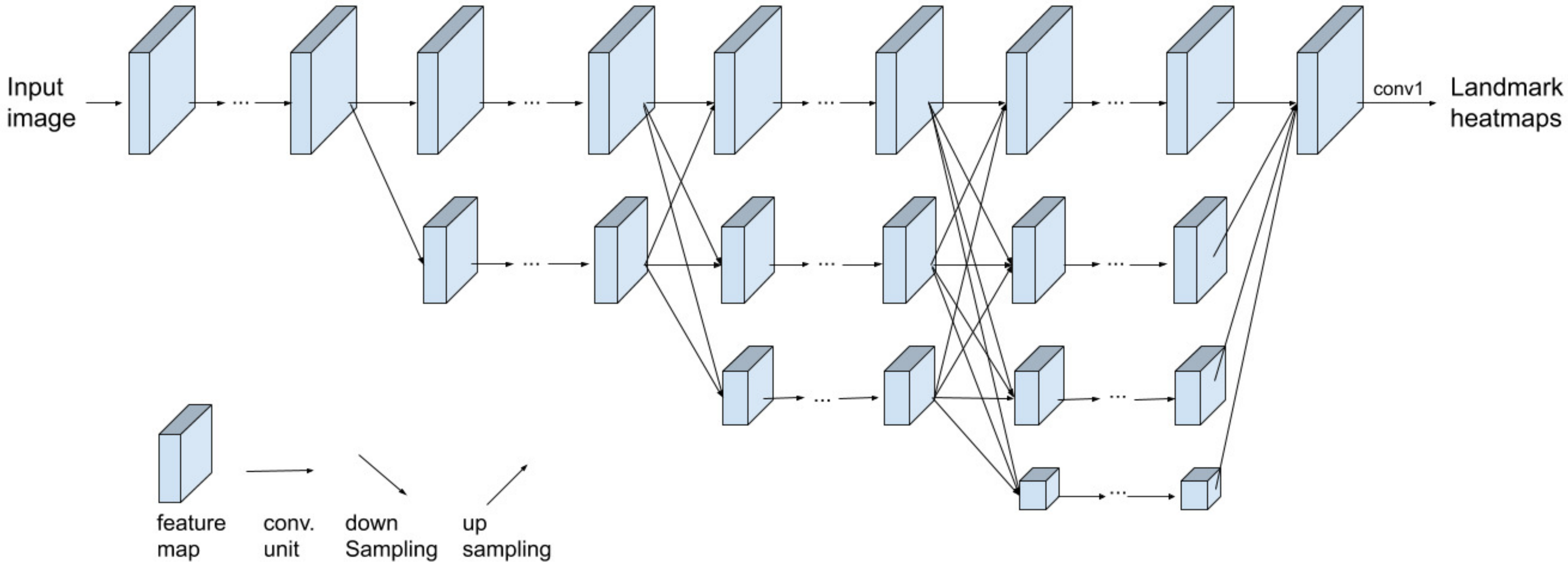
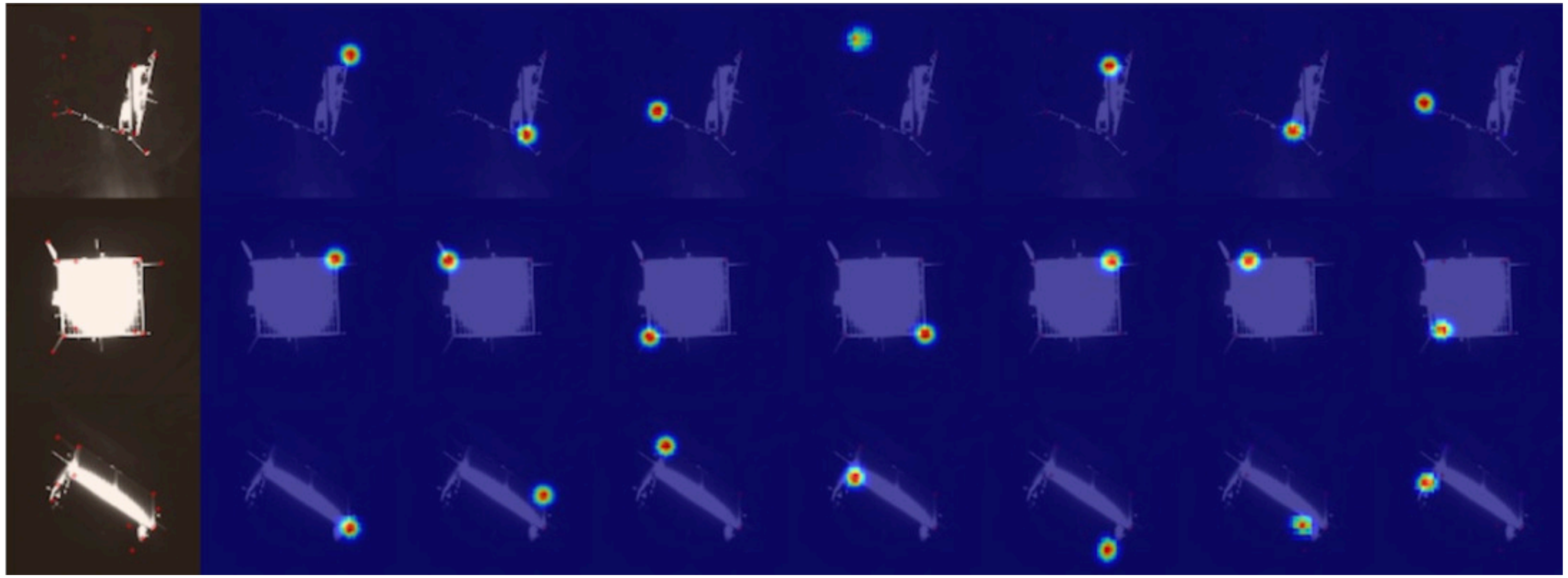
Landmark regression



Landmark regressor



Landmark heatmap loss



$$\ell = \frac{1}{N}\sum_{i=1}^{N} v_i(h(\mathbf{z}_i) - h(\mathbf{z}_i^*))^2$$

Pytorch implementation: https://github.com/BoChenYS/BPnP

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Outline

- Track D: Robot Learning
- Motivation - why simulation in robot learning?
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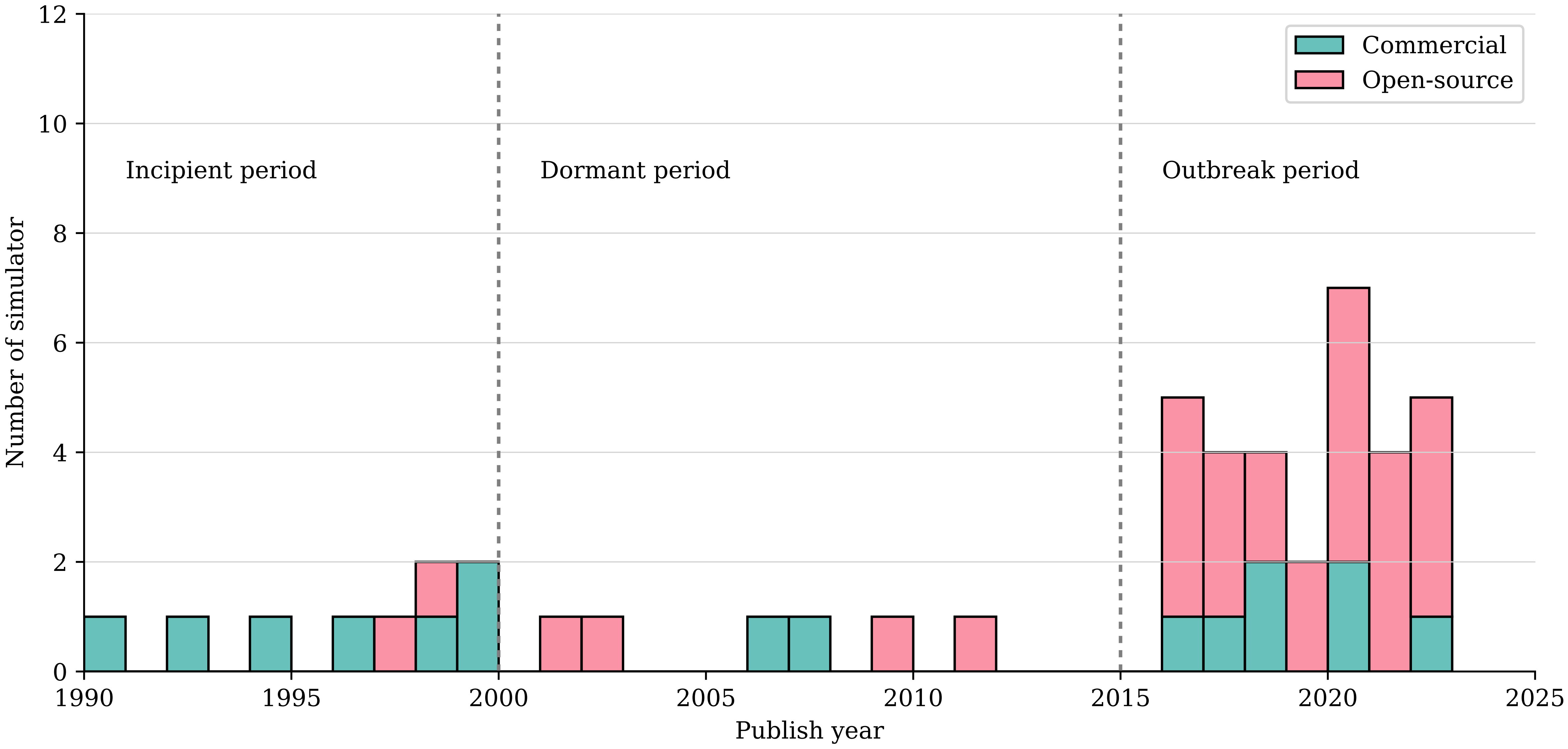
- Popular simulators

No. of simulators for autonomous driving released by year



Y. Li et al., "Choose Your Simulator Wisely: A Review on Open-source Simulators for Autonomous Driving," in IEEE Transactions on Intelligent Vehicles, 2023.

Types of autonomous driving simulators

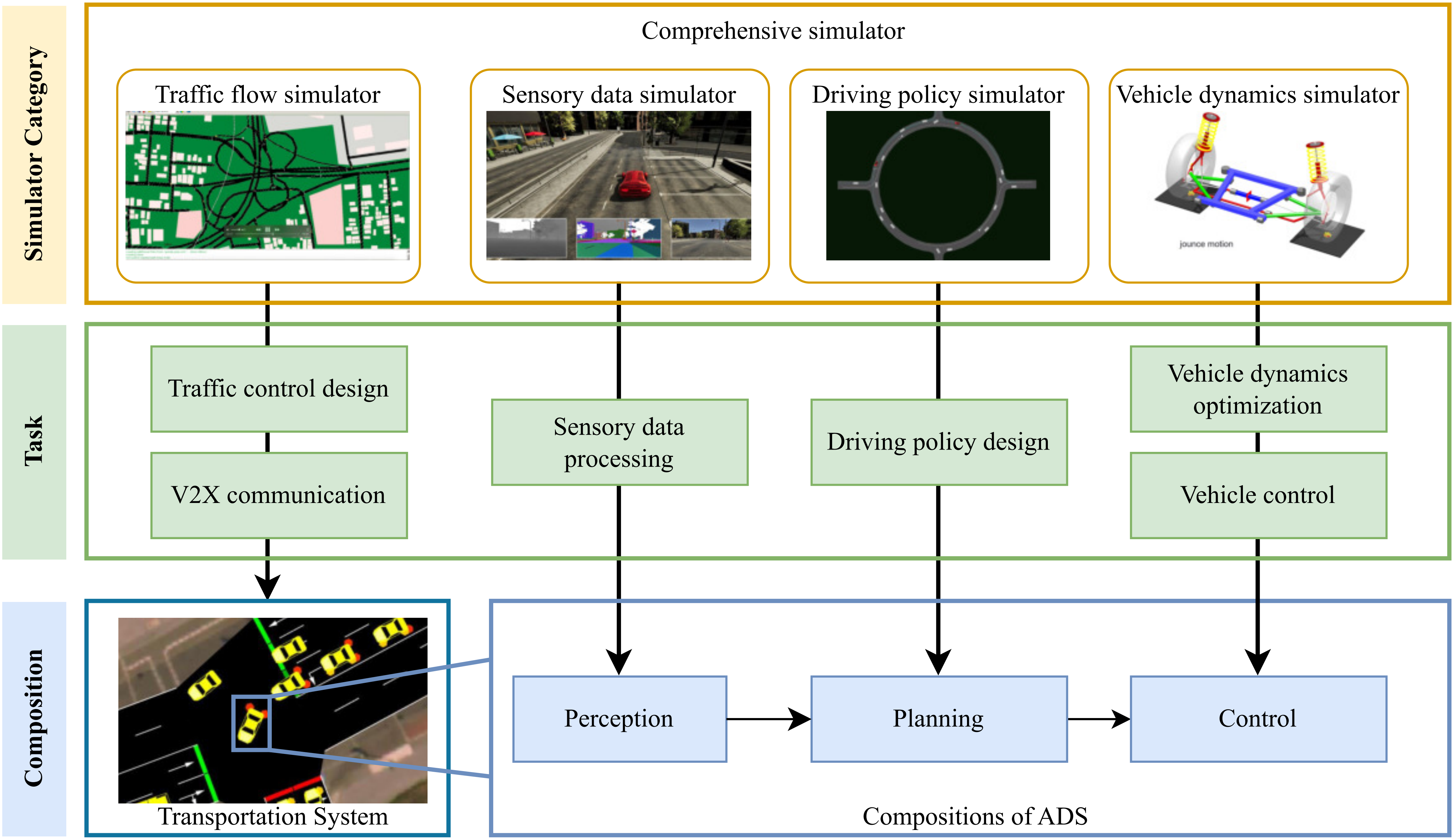


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TABLE I

BASIC INFORMATION OF CATEGORIZED SIMULATORS. FUNCTIONS: ① TRAFFIC CONTROL DESIGN; ② V2X COMMUNICATION; ③ SENSOR DATA PROCESSING; ④ DRIVING POLICY DESIGN; ⑤ END-TO-END DRIVING POLICY DESIGN; ⑥ VEHICLE DYNAMICS OPTIMIZATION; ⑦ VEHICLE CONTROL

Category	Simulator	Released Year	Active Maintenance	Open-source	Related Tasks
Traffic flow simulator	PTV Vissim [31]	1992	√	-	①
	Paramics [32]	1994	√	-	①
	Aimsun [46]	1999	√	-	① ②
	SUMO [37]	2001	√	√	① ②
	POLARIS [47]	2016	√	-	① ②
	Flow [48]	2017	-	√	①
	CityFlow [49]	2019	-	√	①
Sensory data simulator	Sim4CV [50]	2016	-	-	③ ⑦
	AirSim [38]	2017	-	√	③ ④
	Parallel Domain [51]	2017	?	-	③
	SVL [44]	2018	-	√	③ ④
	UniSim [52]	2023	√	-	③
Driving policy simulator	TORCS [53]	1997	-	√	⑤
	VDrift [54]	2011	√	√	⑤
	CarRacing [55]	2016	√	√	④
	Udacity [56]	2016	-	√	⑤
	CommonRoad [39]	2017	√	√	④
	highway-env [45]	2018	√	√	④
	MACAD [57]	2019	?	√	④
	BARK [58]	2020	?	√	④
	DriverGym [59]	2020	-	√	④
	SMARTS [60]	2020	√	√	④ ⑤
	SUMMIT [61]	2020	?	√	④ ⑤
	DI-Drive [62]	2021	?	√	⑤
	L2R [63]	2021	√	√	⑤
	MetaDrive [64]	2021	√	√	④ ⑤
	NuPlan [8]	2021	√	√	④
	InterSim [65]	2022	√	√	④
	Nocturne [66]	2022	?	√	④
	TBSim [67]	2023	√	√	④
	Waymax [9]	2023	√	√	④
Vehicle dynamics simulator	CarSim [34]	1996	√	-	⑥ ⑦
	Webots [68]	1998	√	√	⑥ ⑦
	CarMaker [35]	1999	√	-	③ ⑥ ⑦
	Gazebo [69]	2002	?	√	⑥ ⑦
	VI-CarRealTime [41]	2009	√	-	⑥ ⑦
	Matlab [70]	2018	√	-	⑥ ⑦
Comprehensive simulator	SCANeR Studio [71]	1990	√	-	③ ④ ⑤ ⑥ ⑦
	Virtual Test Drive [72]	1998	√	-	③ ④ ⑤ ⑥ ⑦
	PreScan [40]	2006	√	-	③ ④ ⑤ ⑥ ⑦
	rFpro [36]	2007	√	-	③ ⑤ ⑥ ⑦
	CARLA [7]	2016	√	√	③ ④ ⑤ ⑦
	DeepDrive [73]	2018	?	√	③ ④ ⑤ ⑥
	Nvidia Drive Sim [74]	2020	√	-	③ ⑤ ⑥ ⑦
	Vista [75]	2020	√	√	③ ⑤
	VI-WorldSim [41]	2020	√	-	③ ④ ⑤ ⑥ ⑦

Y. Li et al., "Choose Your Simulator Wisely: A Review on Open-source Simulators for Autonomous Driving," in IEEE Transactions on Intelligent Vehicles, 2023.

CARLA (https://carla.org/)

Nvidia Drive Sim (https://developer.nvidia.com/drive/simulation)

Fidelity of simulation

Fig. 4. A comparison of real-world and simulated RGB images in day, night, rainy, and foggy weather. The first row are from BDD100K dataset and the second row is from CARLA [7, 93]

Y. Li et al., "Choose Your Simulator Wisely: A Review on Open-source Simulators for Autonomous Driving," in IEEE Transactions on Intelligent Vehicles, 2023.

make history.

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