TT-bot

Autonomous Mobile Robot for Indoor Object Collection

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*Research was conducted as a part of NAVER LABS Research Internship Program

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Objective

- Develop an Autonomous Mobile Robotic System for Indoor Object Collection
  - Selectively collect target objects
  - Ball collection or warehouse management
- Compact Mechanical Design and Efficient End Effector for Indoor Operation
  - Small sized (0.4m x 0.4m) robotic platform
  - Robust collection process with suction-based end effector
- Deep Learning-based Perception and Motion Planning for better performance
  - Developed novel structure ADCN & GRL-planner to integrate Deep Learning

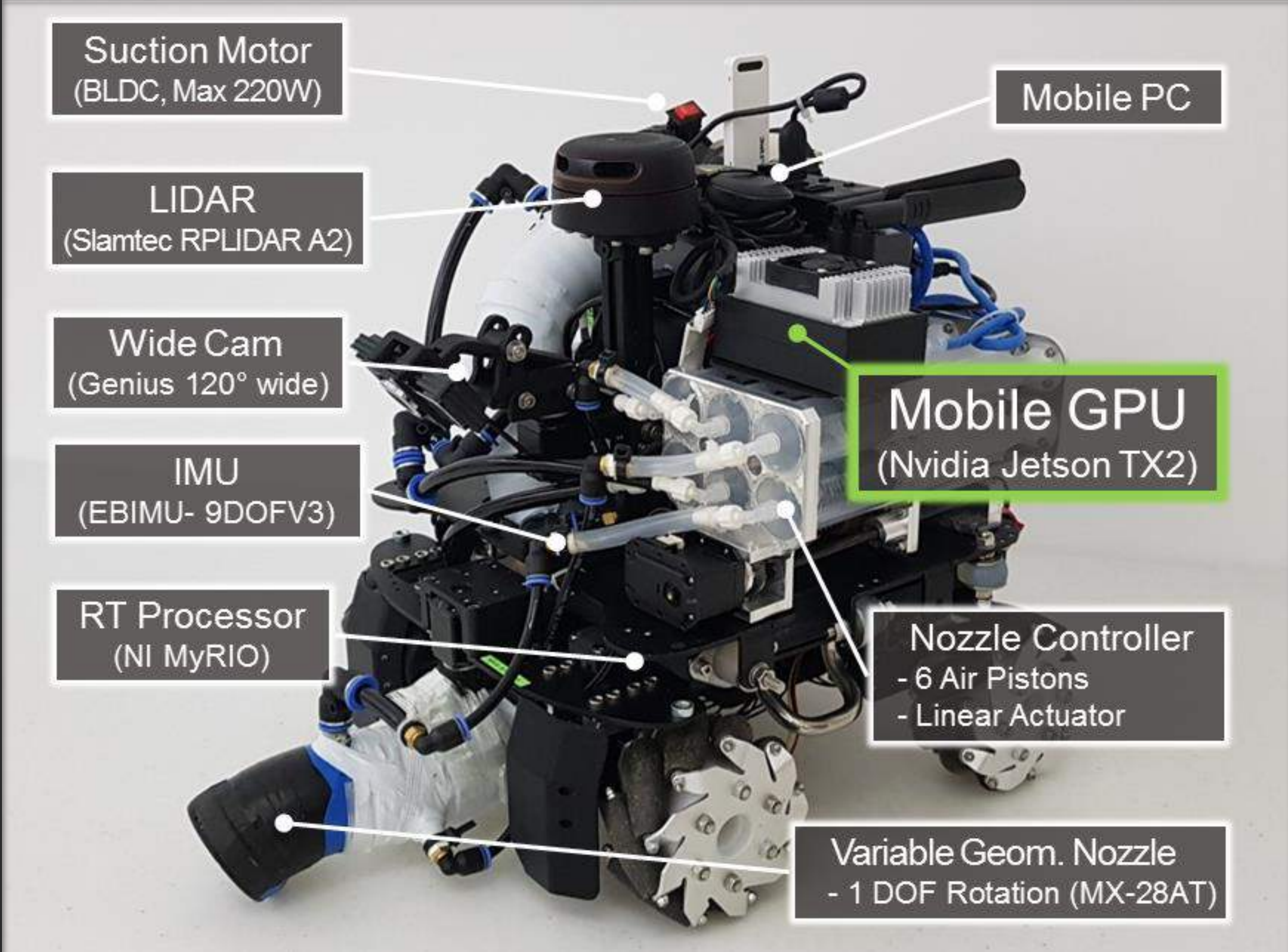
TT-bot

Small-sized

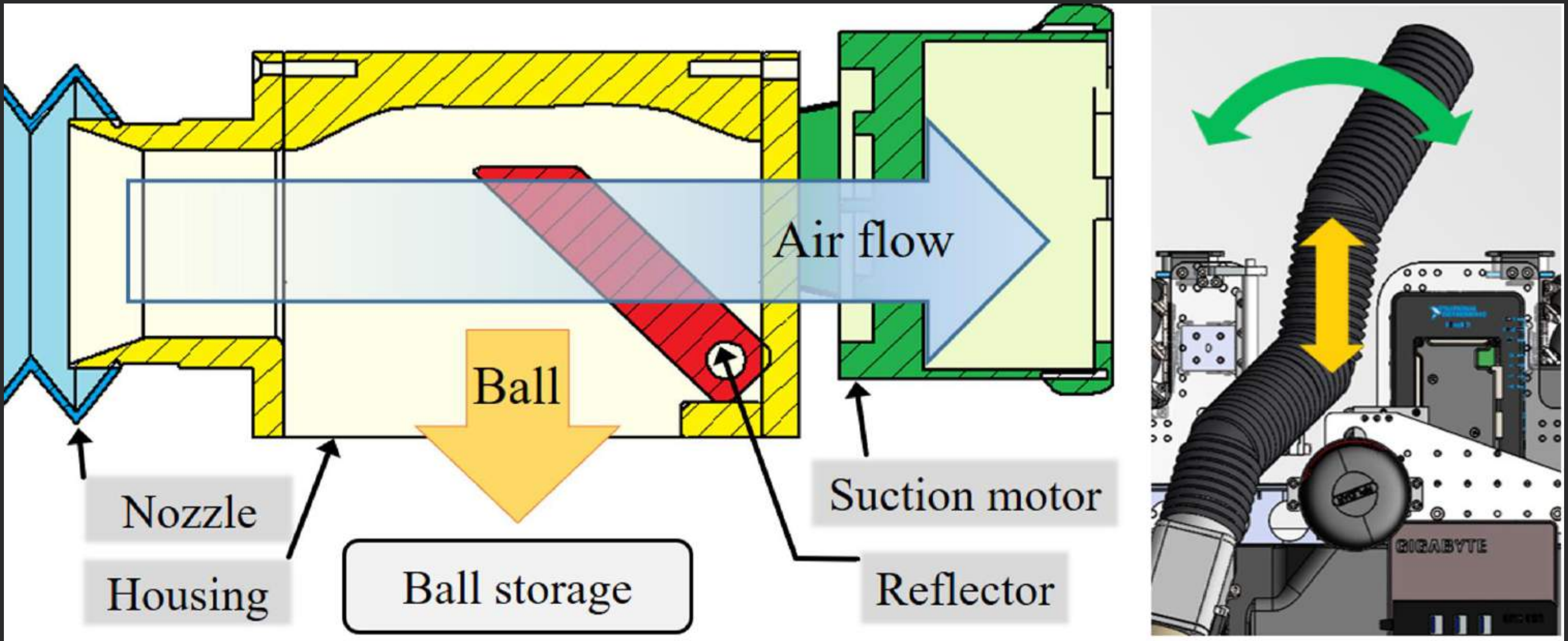
Standalone

Intelligent

Mobile Robot

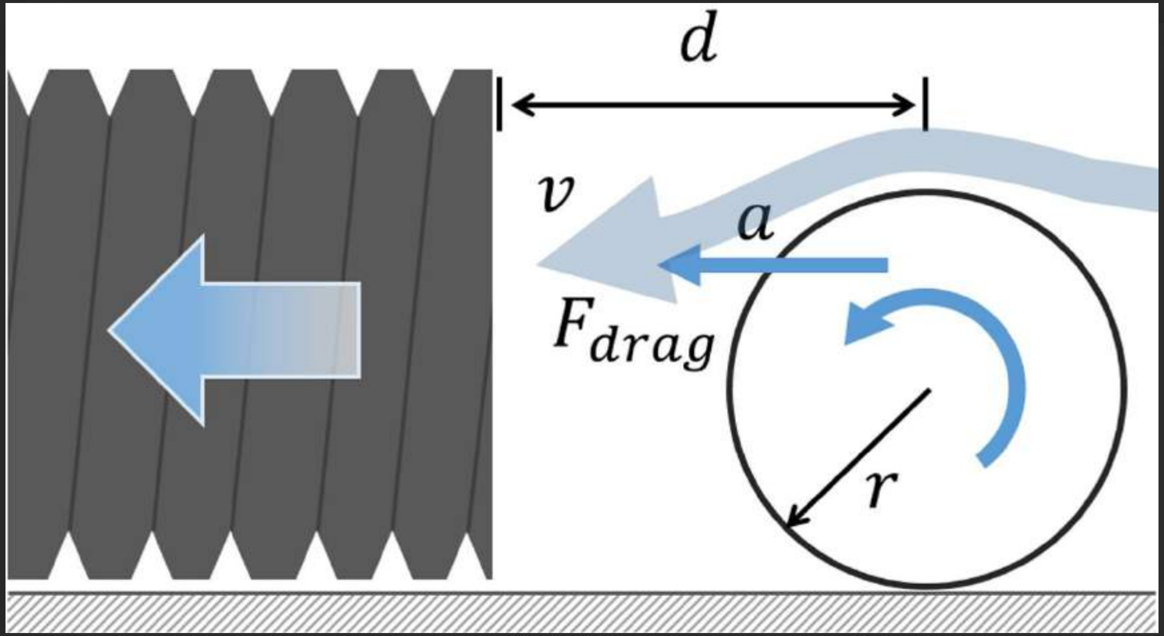


Hardware – Object Collection



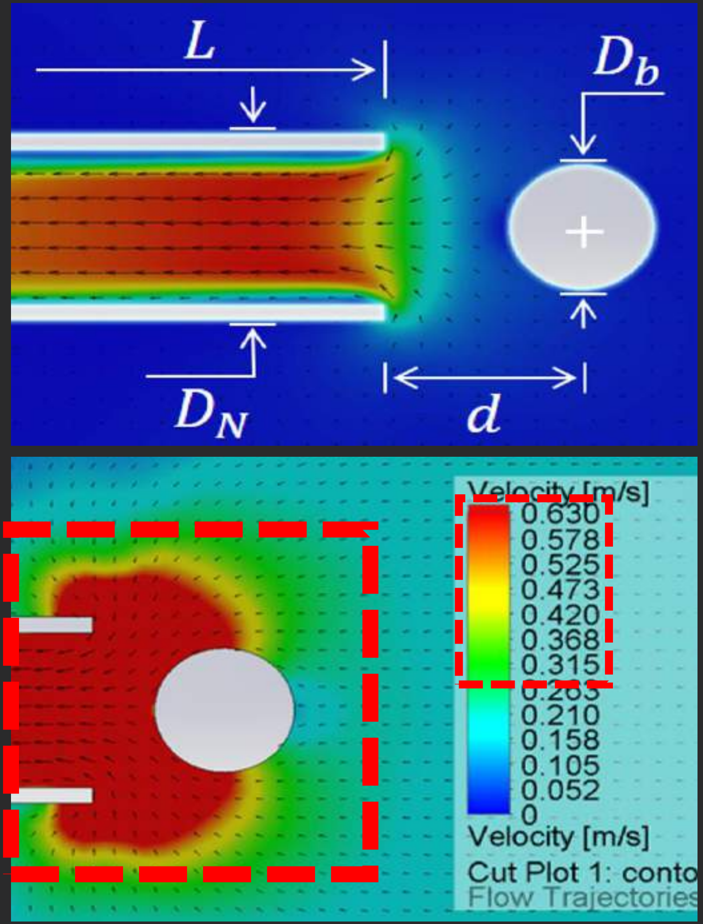
Object collection module with suction motor and reflector

Hardware – Design Principle of Collection



- Power Consumption is Optimized
- Coverage ~ 50 X 50 mm
- Duration < 2s
- The onset of motion is triggered by Rolling
- Torque is induced by Drag Force

Hardware – Design Principle of Collection



$$d \leq \frac{1}{2}a\tau^2 \quad (1)$$

$$T = \alpha r F_{drag} \quad (2)$$

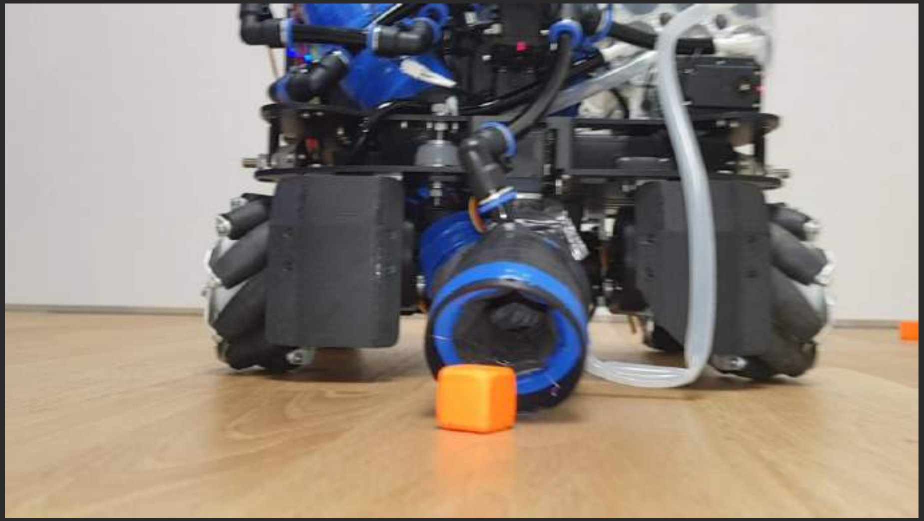
$$v^2 \geq \frac{4d(I_b + m_b r^2)}{\alpha\tau\rho C_D \pi r^4} \quad (3)$$

Table 1 System parameters

Notation	Description	Simulation Value
m_b	Mass of a ball	2.7 g
I_b	Moment of inertia	7.13×10^{-7} kg m^2
r	Radius of a ball	20 mm
ρ	Density of air	1.29 kg m^{-3}
v	Inhalation flow speed	0.71 m s^{-1}
C_D	Drag coefficient	0.47
α	Correction factor	0.5
d	Valid range	40 mm
τ	Valid time limit	2 s
T	Torque w.r.t. ground	

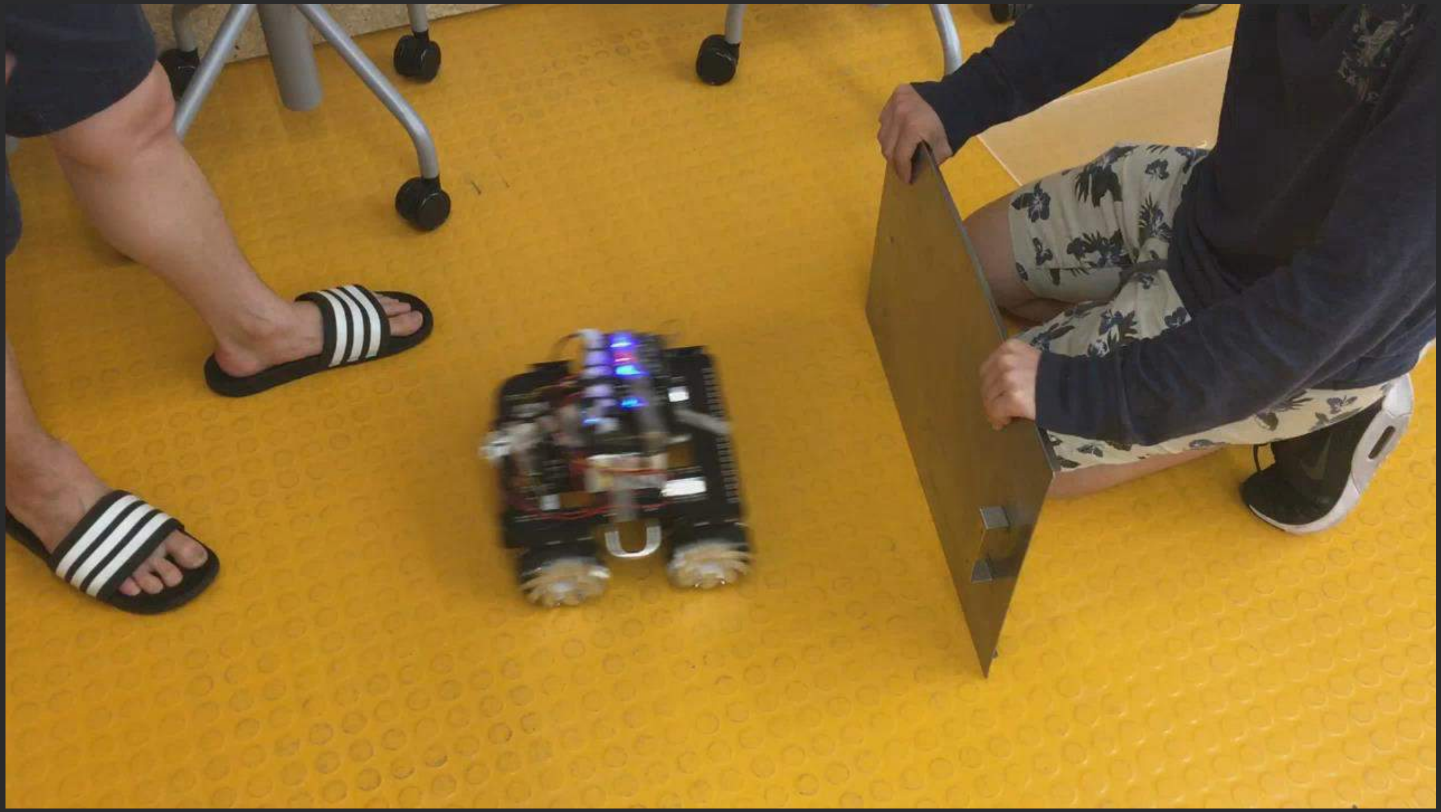
System verification with Computational Fluid Dynamics (CFD) simulation

Hardware – Variable Geometry Nozzle

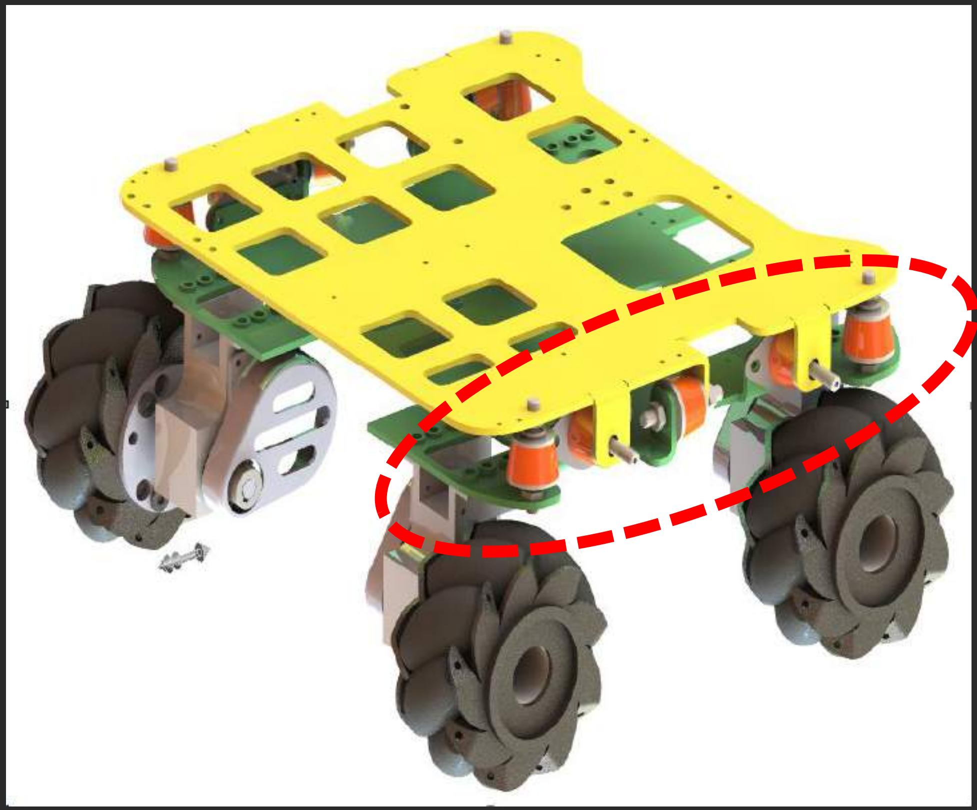


- Install the inner membrane of latex material
- Control the air between membrane with piston controller
- Optimize inner radius to the target's size
- Minimize the loss of hydraulic pressure

Hardware – Platform



Mecanum Wheel for Holonomic movement



3-axis damper for simple suspension

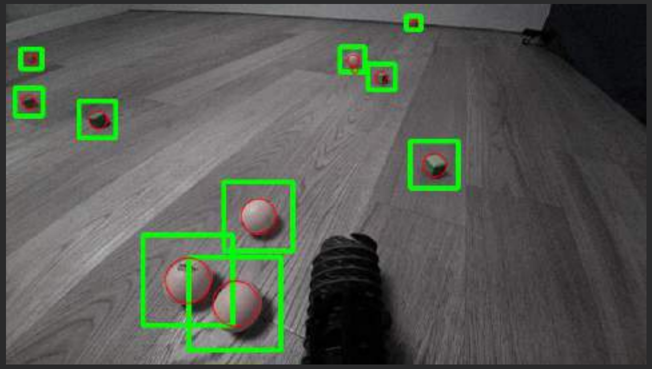
Software

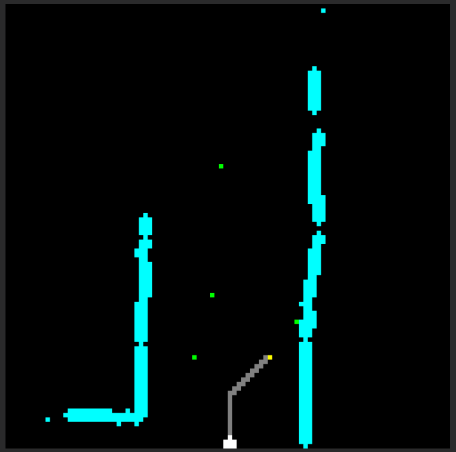
- How to improve detection accuracy?
- How to deal with not precise enough virtual map?
- What is a best decision for various conditions?

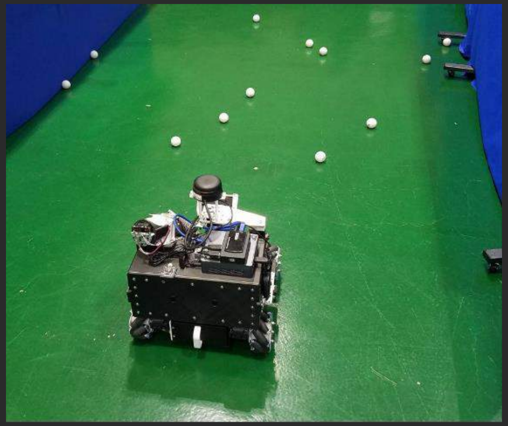
→ Deep Learning Technology

Software - Overview

Sensing → Perception → Decision Making → Planning → Actuation





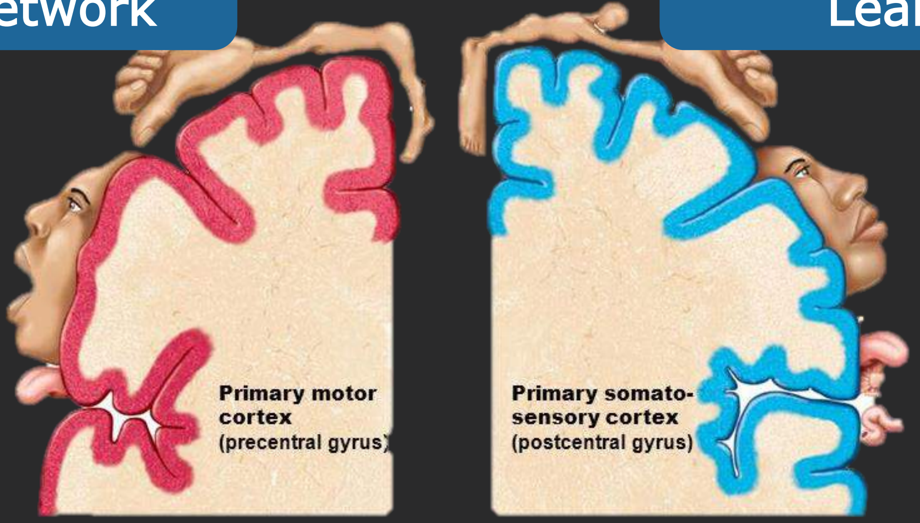


“Deep Learning”

Sensing → Perception → Decision Making → Planning → Actuation

Deep Convolutional Neural Network ↑ (Perception)

Reinforcement Learning ↑ (Planning)



Software

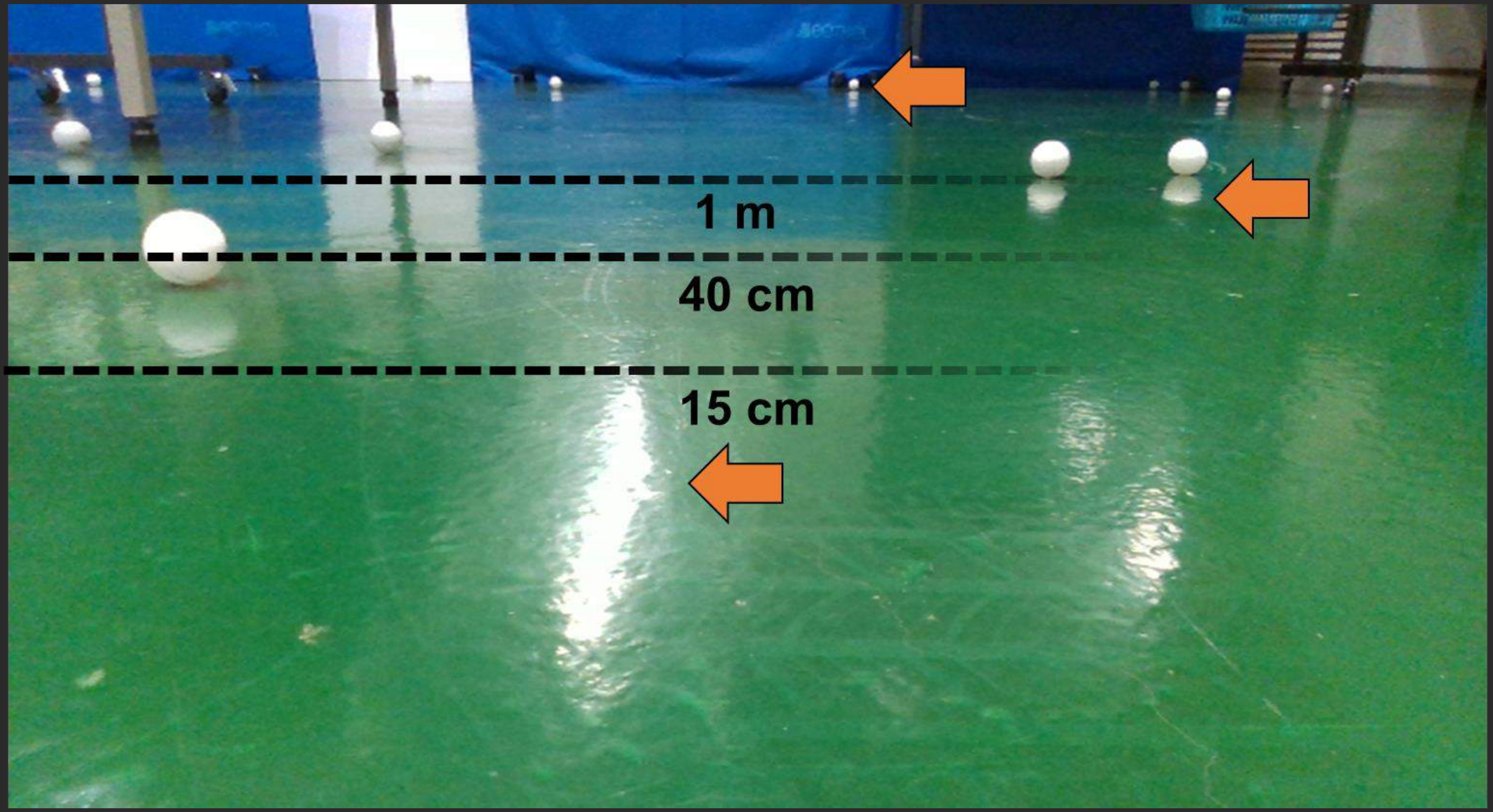
Sensing

Perception

Decision Making

Planning

Actuation



Obstacle abundant environment & Limited resolution

Software

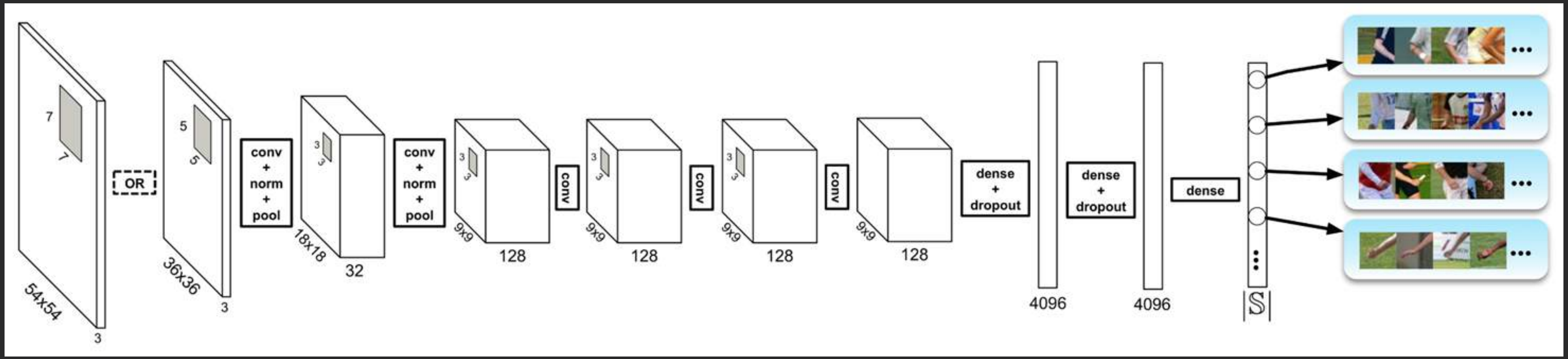
Sensing
↓
Perception
↓
Decision Making
↓
Planning
↓
Actuation

Obstacle abundant environment & limited resolution
→ Highly precise objection classification algorithms are required!

Software

- Sensing
- **Perception**
- **Decision Making**
- Planning
- Actuation

Deep Convolutional Neural Network (DCNN)



Software

DEEP CLASSIFIER COMPUTATION TIME COMPARISON

Processor	Computation Time [ms]			
	batch 1	batch 4	batch 8	batch 16
Intel i5-5600U	1560	5800	11000	-
Jetson TX2 Max-P	125	360	710	1430
Jetson TX2 Max-N	110	315	590	1230
Nvidia GTX 960	30(40*)	92(100*)	175(195*)	340(365*)
Nvidia Titan X	25(35*)	82(91*)	163(183*)	295(380*)

Stand-alone robotic system with DCNN?

→Mobile GPU Jetson TX2

Software

Sensing

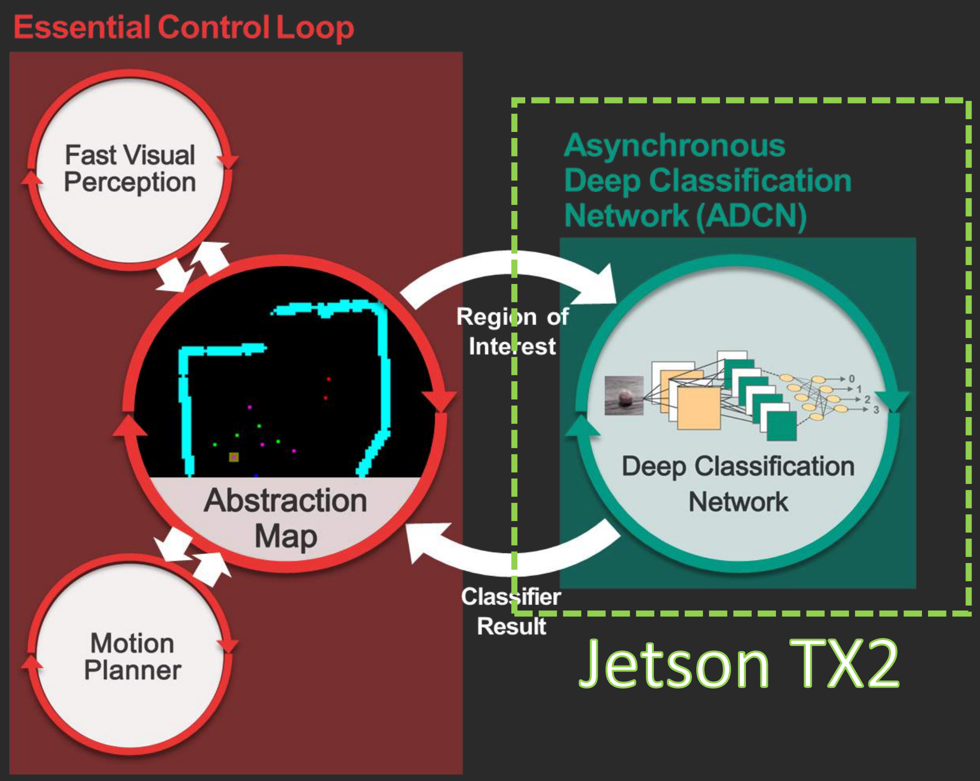
Perception

Decision Making

Planning

Actuation

Framework for Asynchronous Deep Classification Network (ADCN)



To enhance Jetson TX2's performance,
Asynchronously operate DCNN

Software

Sensing

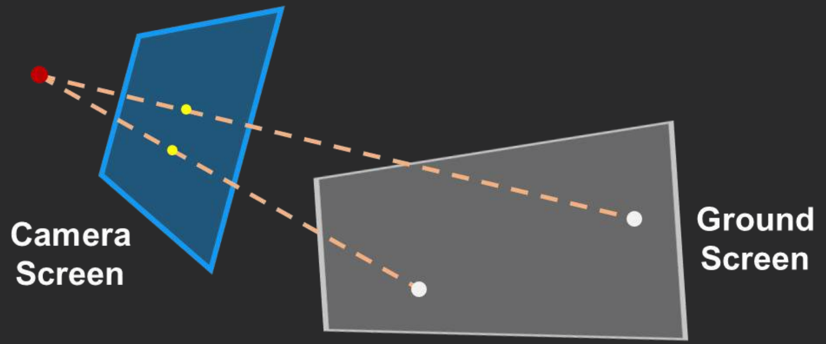
Perception

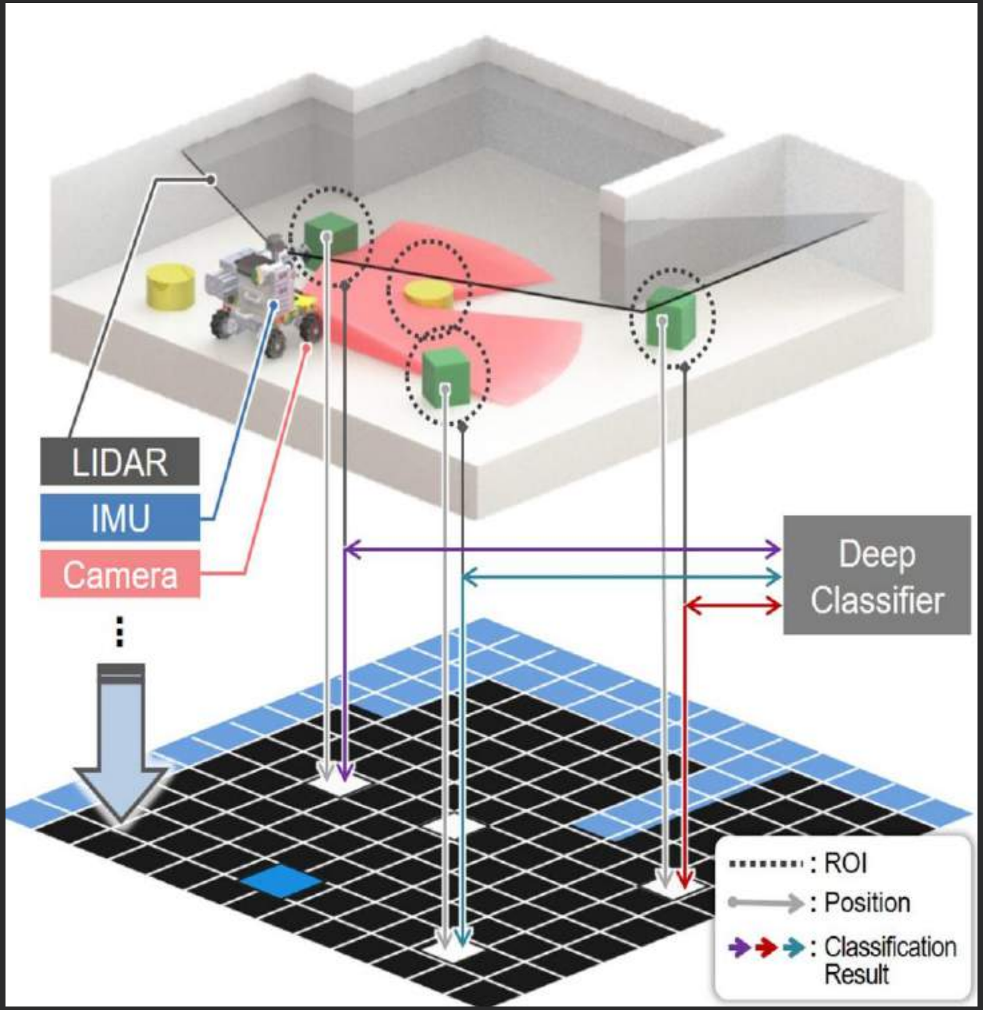
Decision Making

Planning

Actuation

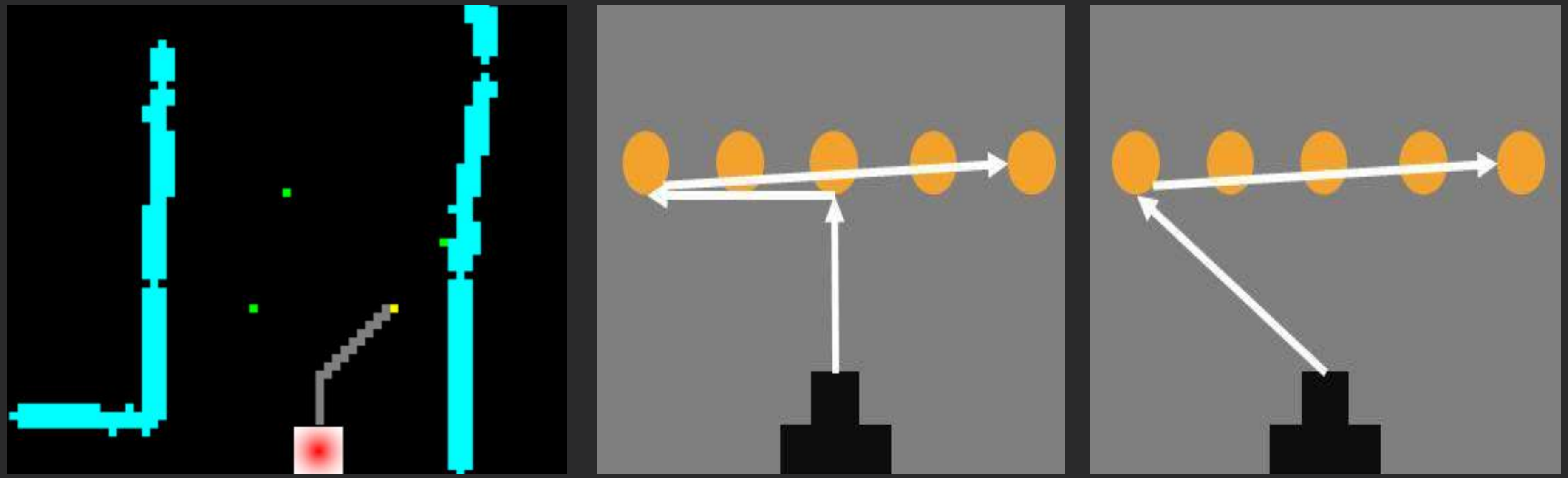
Occupancy Map → Hub for Sensor Data Integration





Software

Problems in Motion Planning



Partially Observable & Multiple Target
→ Optimize robot's motion with
Reinforcement Learning

Software

Sensing

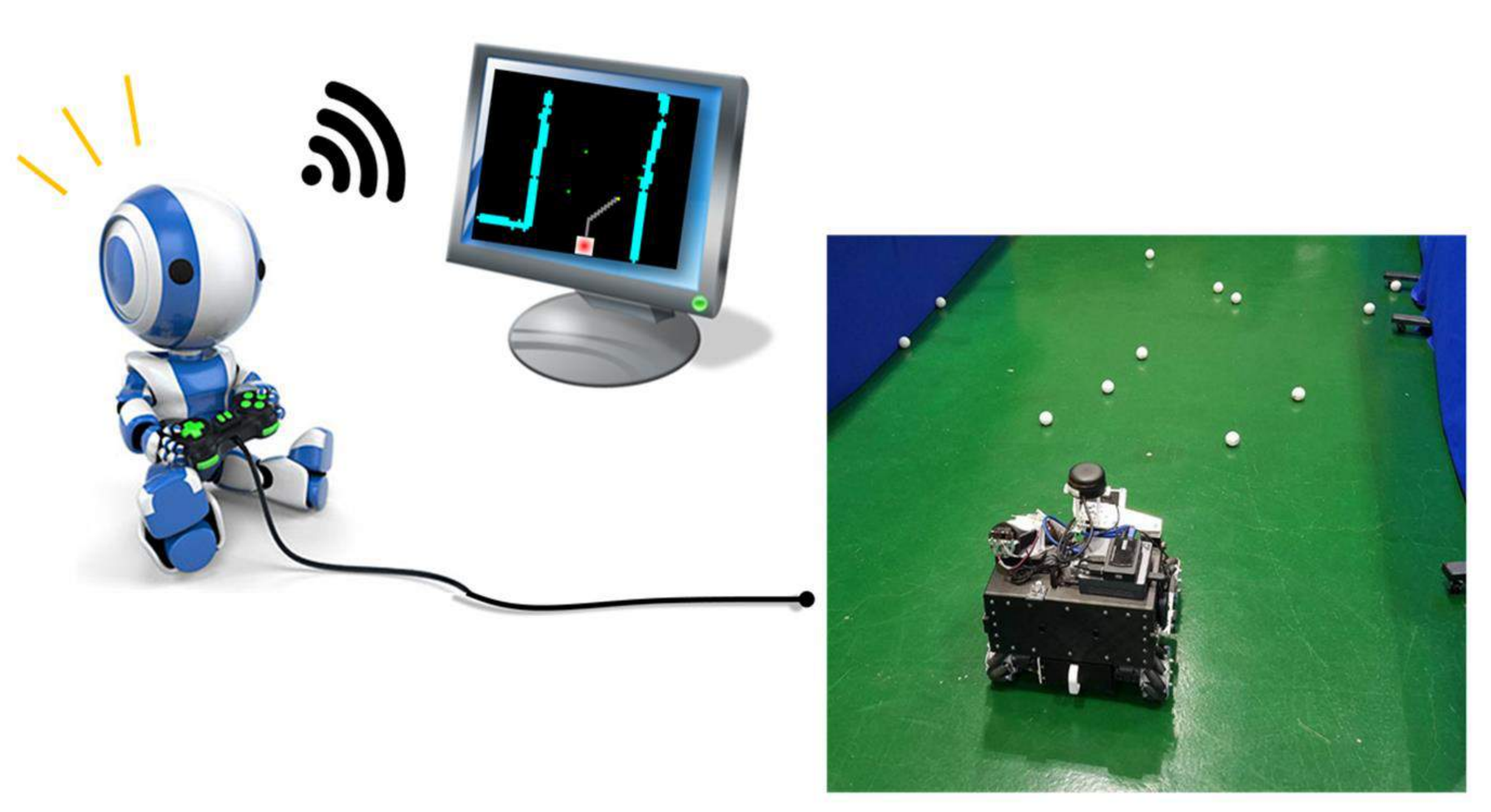
Perception

Decision Making

Planning

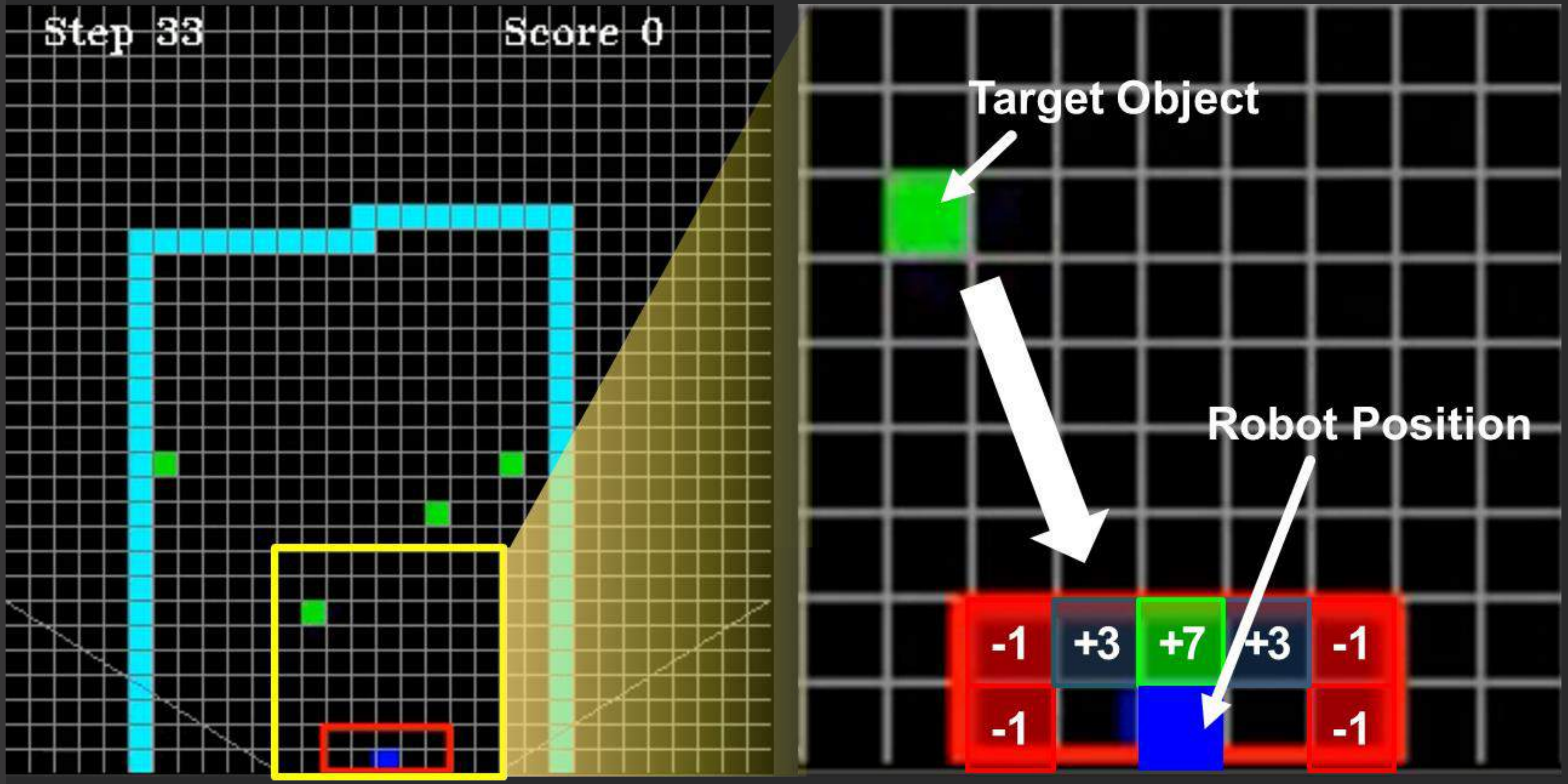
Actuation

Reinforcement Learning



Input : Occupancy Map & Output : game pad command

Software

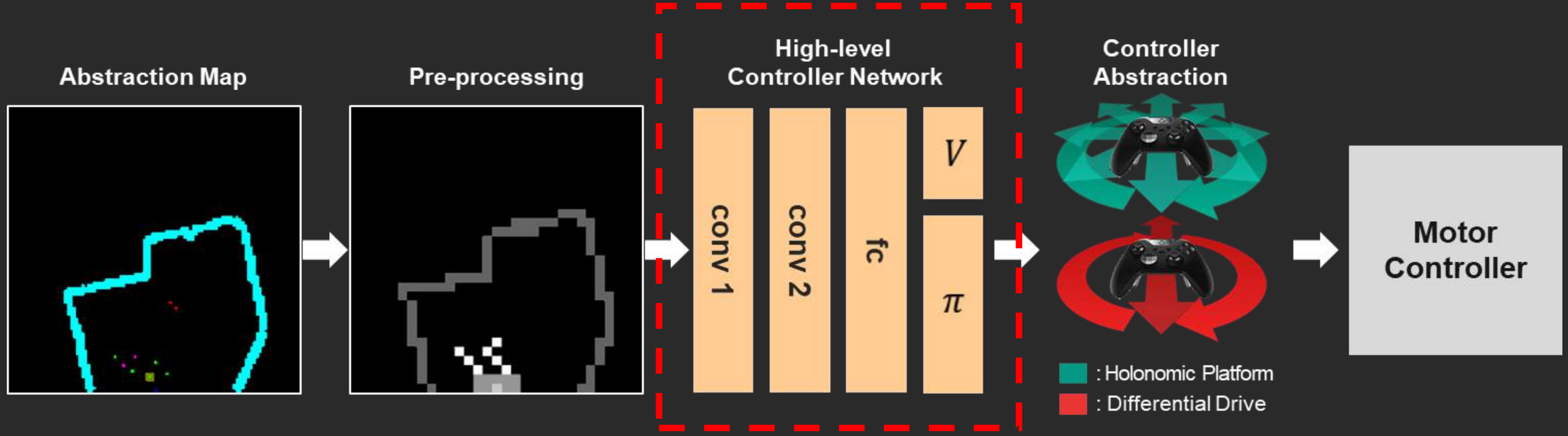


Train the RL network on simulation

→ Reduce training time

Software

Gaming Reinforcement Learning-Based Motion Planner (GRL-planner)



- Utilize occupancy map as an input of RL network and game pad controller signal as an output

- Available on various mobile platform (Holonomic, Differential)

Software

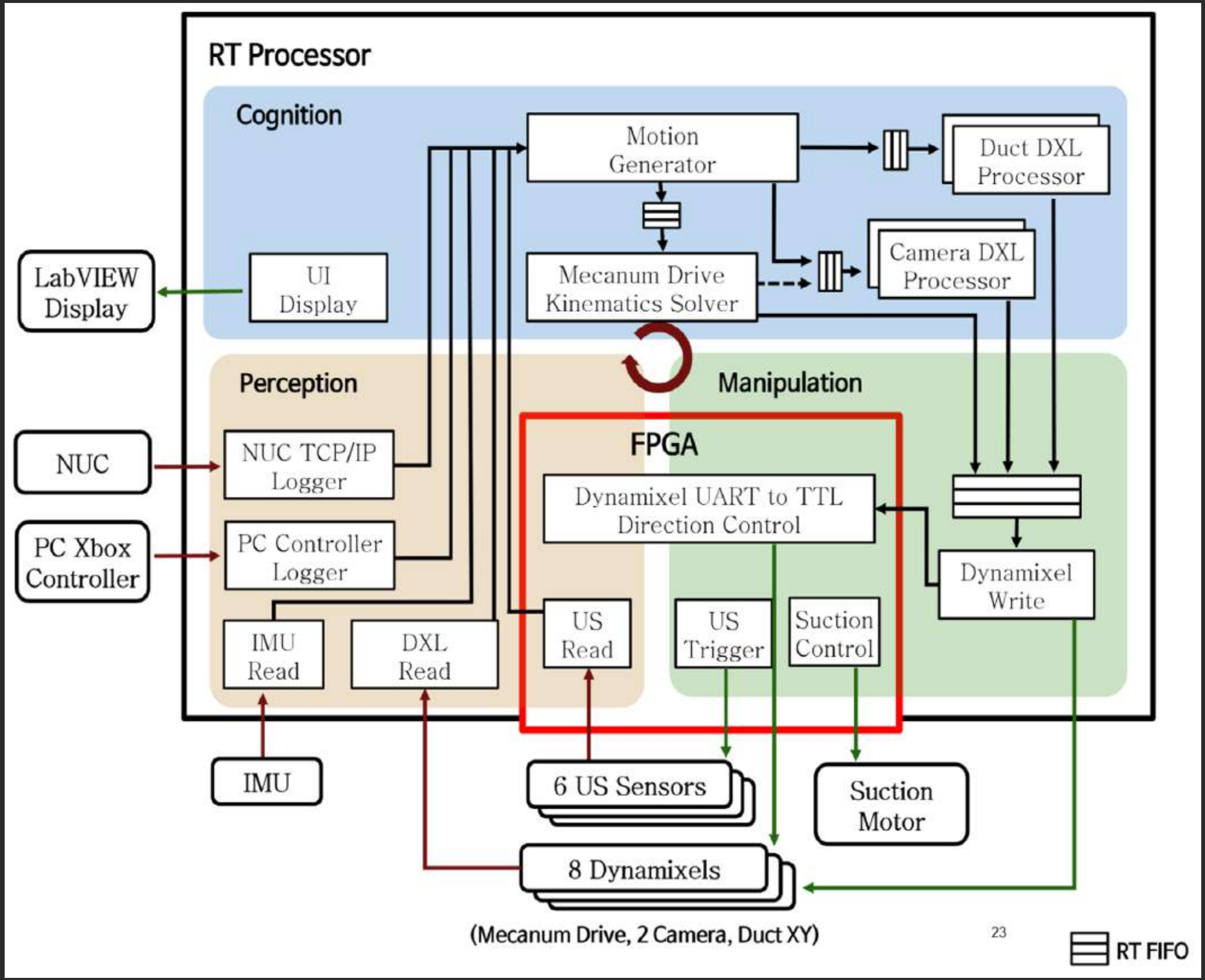
Sensing

Perception

Decision Making

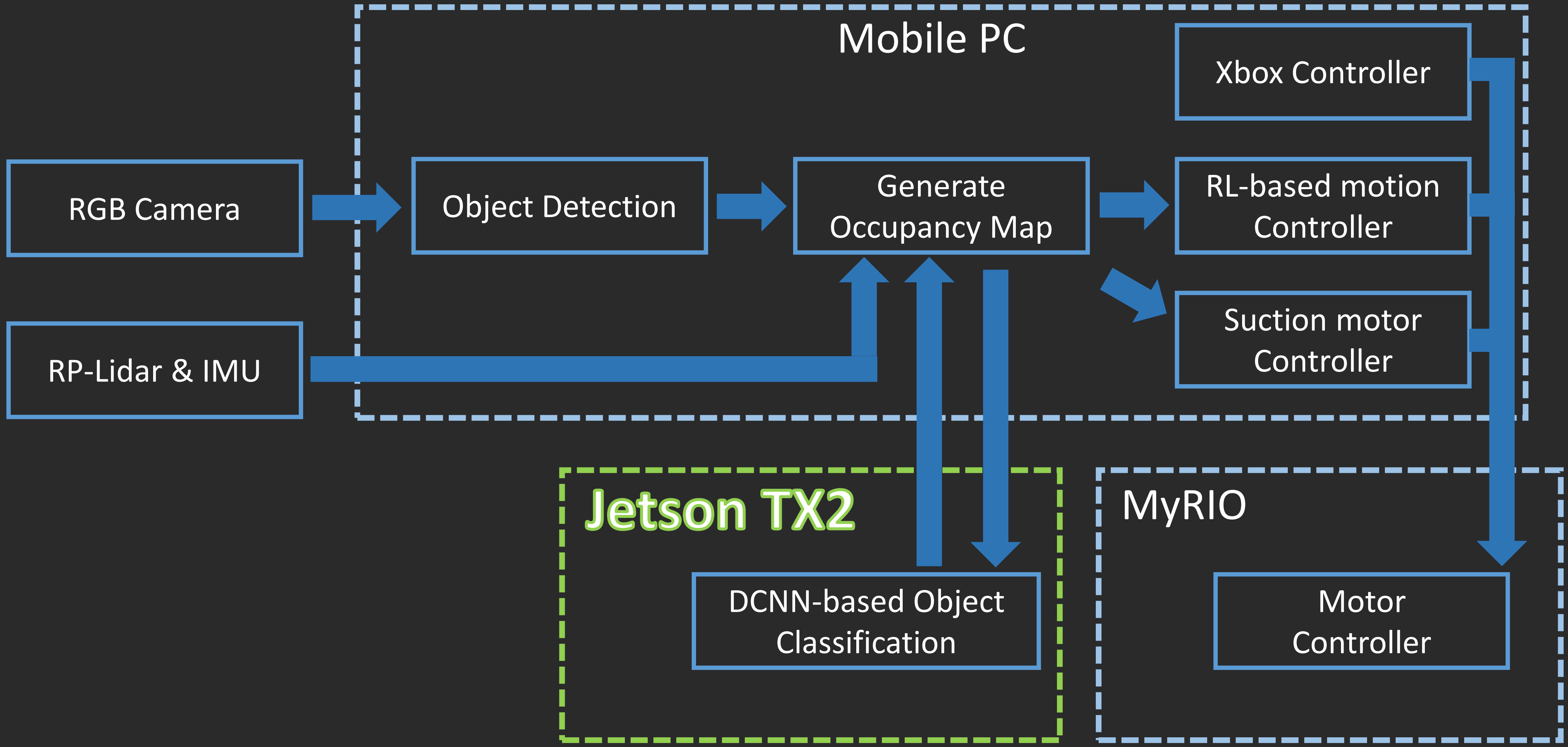
Planning

Actuation

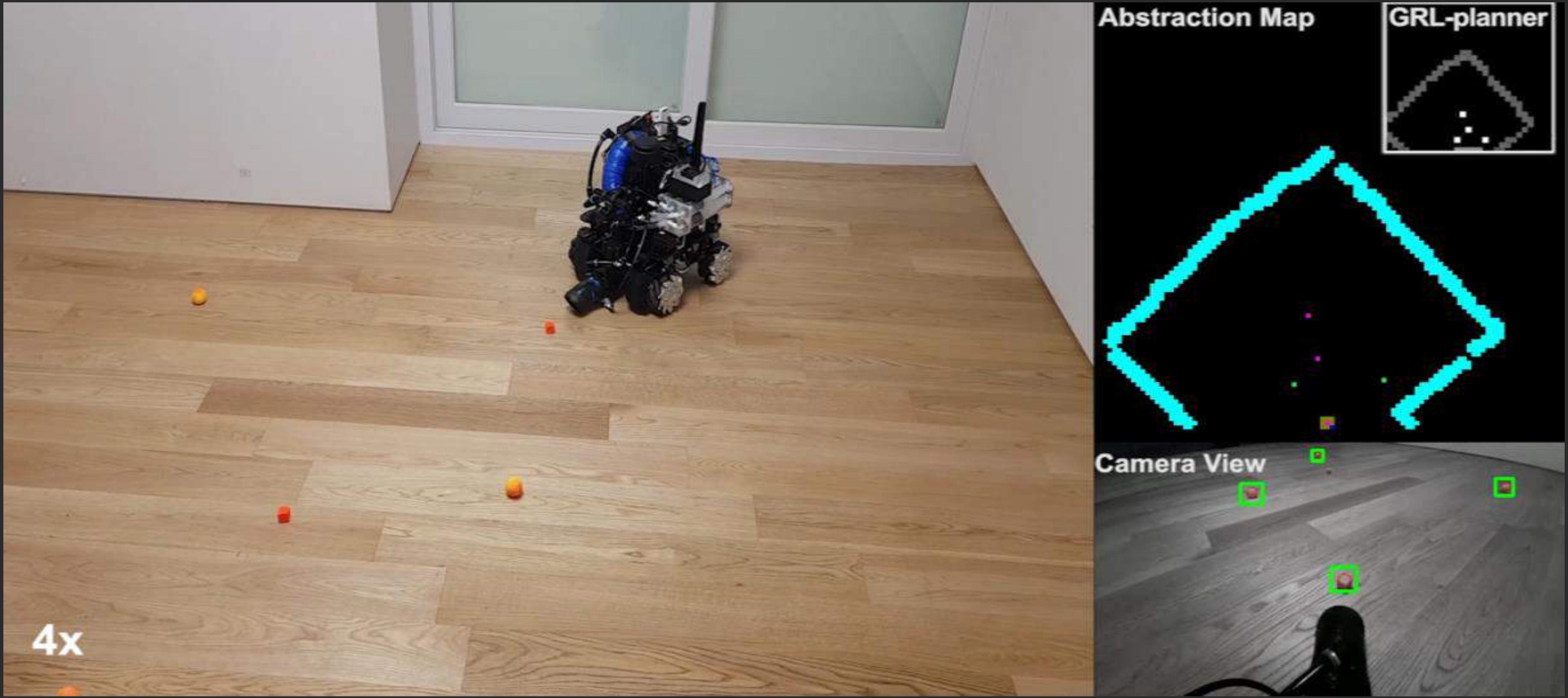


- Developed motor controller with Real Time Processer(MyRio)

Software – Overall Implementation



Software – Overall Implementation



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