Methods In DDC

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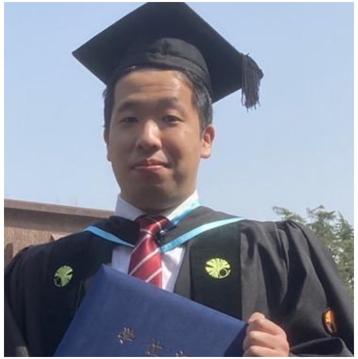
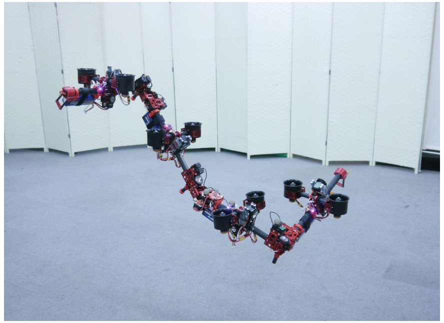
Aerial Robot Team

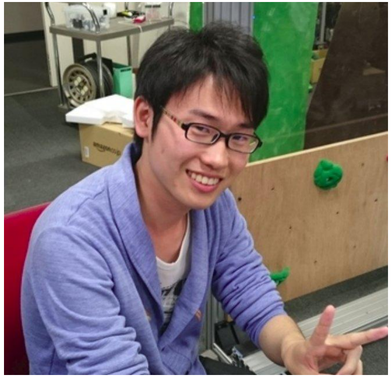
Who we are



Haruki Kozuka
Master student



Moju Zhao
Dragons' guy



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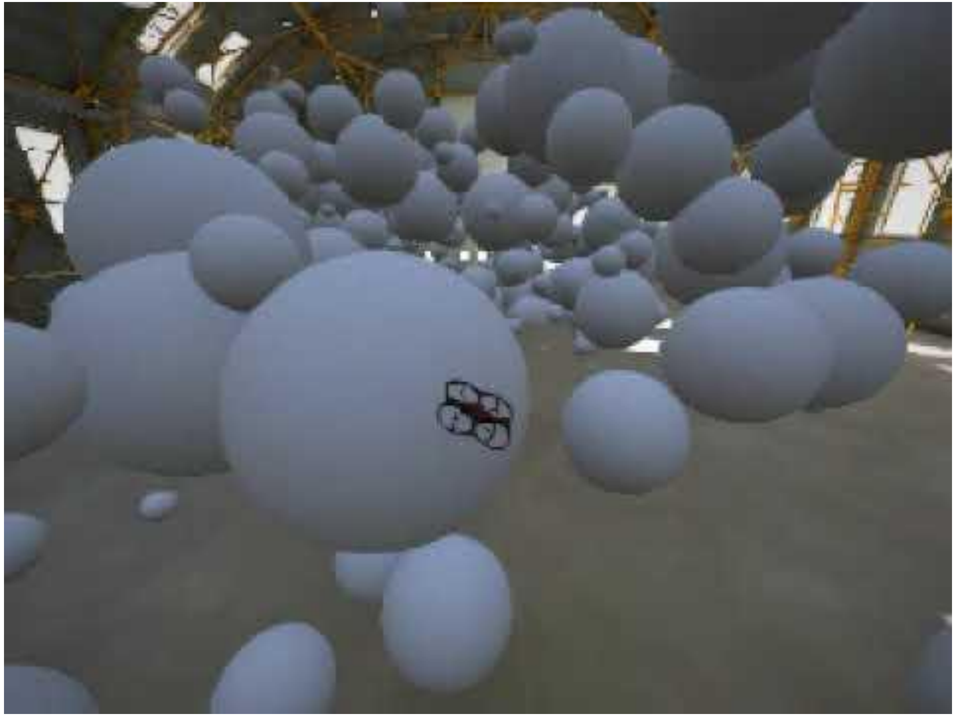


Basic Information of DDC

ROBOTICS & PERCEPTION GROUP

- Drone navigation competition
- Objective: Reach Goal (x > 60) w/o clashing obstacles
    - Success rate, goal time
- Benchmark for autonomous drone navigation
- 3 learning level (easy,medium,hard)

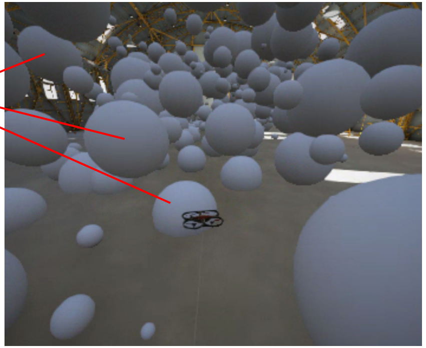
Champion at state-based category

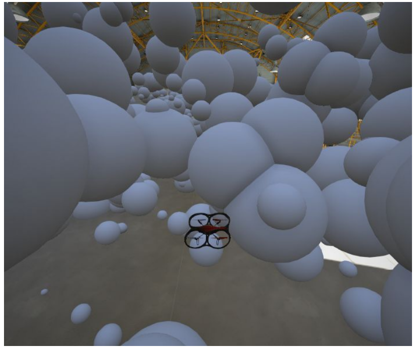

ICRA2022
@ieee_ras_icra

Congrats to the winners of the DodgeDrone Challenge - Yvo Keuter from TU Delft and Haruki Kozuka from University of Tokyo! Learn more about the competition in

Twitter: ICRA 2022

Obstacle


medium


hard

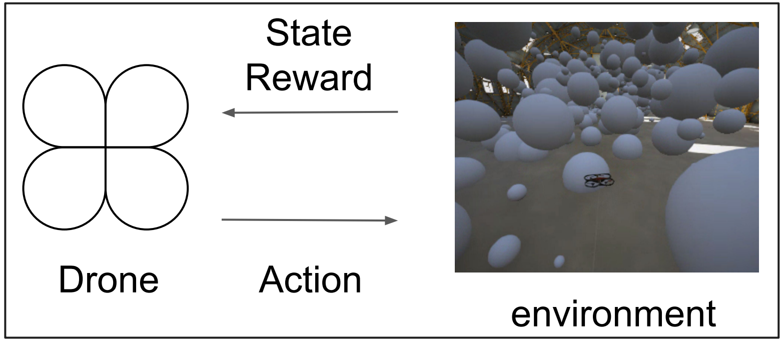
Initial RL Setting offered by the DDC organizers

Our method is Reinforcement Learning(RL) based approach

State	dimension
10 obstacles' Center & size	40 (=10*(3+1))
desired velocity	3
orientation, velocity	9+3
sum	55

Action	dimension
Bodyrate(ω)	3
full thrust	1
sum	4

Reward
survive reword
collision penalty
velocity penalty (linear&angular)



Main changes from Initial Code

State:

- Obstacle information: polar voxel

Reward:

- reward by moving x direction
- penalty when approaching boundary
- eliminate survive reward
    - disturb moving x direction (stay initial position)

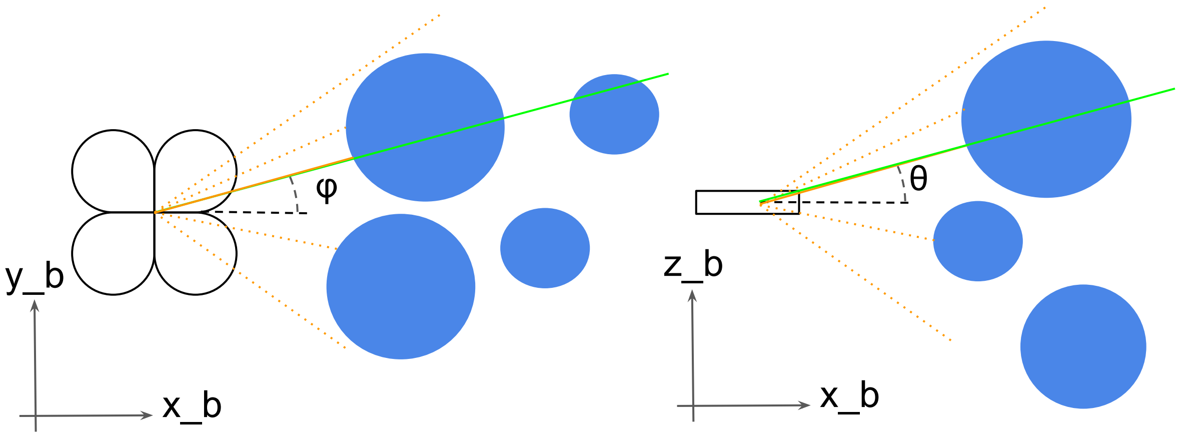
learn only in **medium** environment:

- learn in **hard** -> move slowly

State	dimension
Obstacle (Polar voxel)	64 (= 8*8)
distance from boundary(y,z)	2+2
position,attitude, (linear angular) velocity	3+3+9+3
goal velocity	3
Sum	89

Reward
x move reward
boundary penalty
collision penalty

Create Polar Voxels



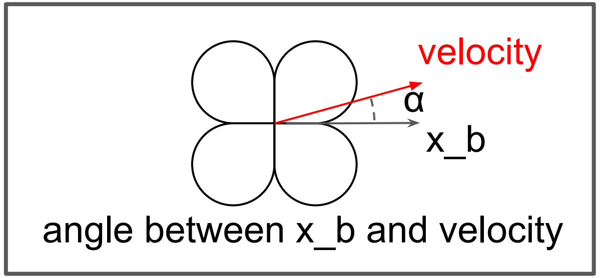
Algorithm

1. set direction (φ, θ)
2. extend straight line in 1's direction
3. calculate distance from closest obstacle
4. do 1~3 in different direction

φ,θ's characteristic

range	-45deg ~ 45 deg
Cuts	8
Output dimension	8*8 = 64

Create Polar voxels



Why θ,φ is -45deg ~ 45deg?

- In most flight, |α|< 45deg
- Quadrotor needs only obstacles' info in velocity's direction if obstacle is static

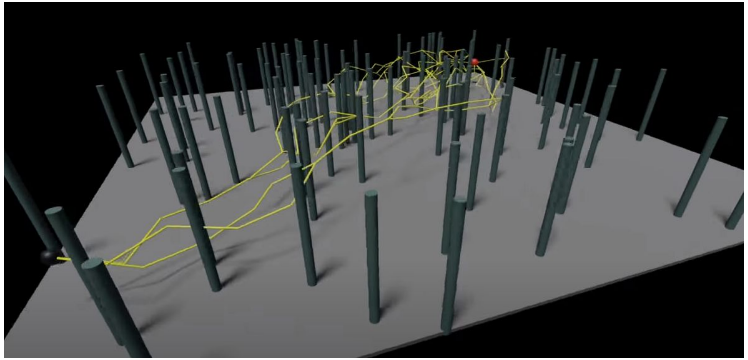
-> Not think about other obstacles' info

interpretation of our method

Check various direction's obstacle

≃ think about desired moving direction

(Cf. topological path search)



Robert Penicka et al. "Minimum-Time Quadrotor Waypoint Flight in Cluttered Environments" (2022)

Flying Result (submission policy)

Test 100 times

medium

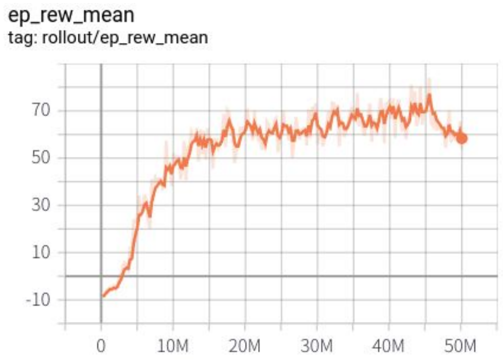
Goal rate: 77

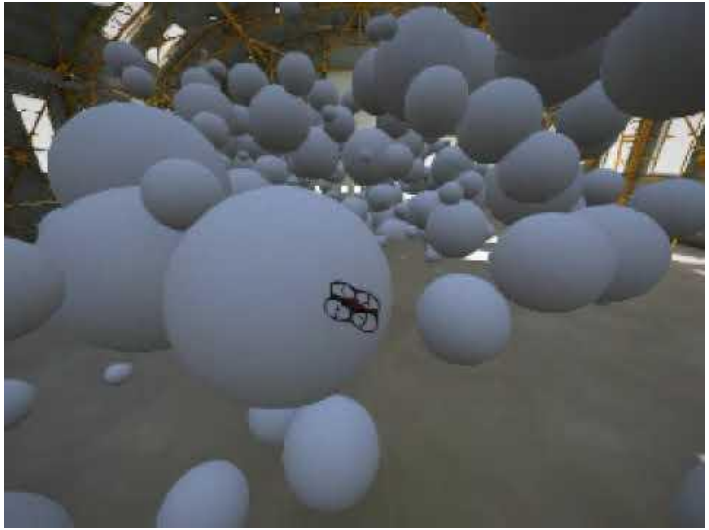
Failure: collide:16, bound: 7, time: <10s

hard

Goal rate: 26

Failure: collide:65, bound: 9

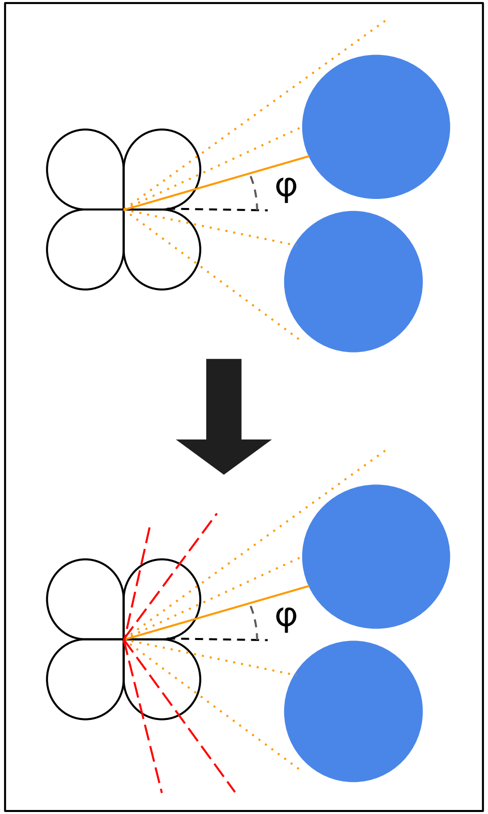




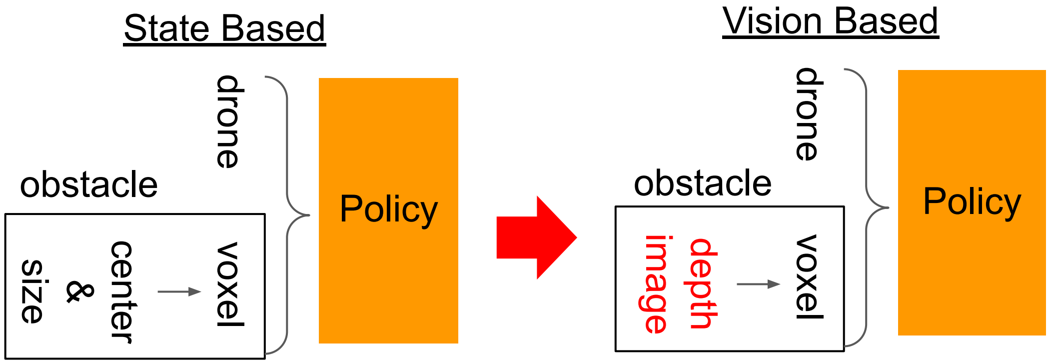
Ideas which do not work well

- Increasing viewing angle
  - because quadrotor collides on their side
  - φ, θ: -45~45 deg -> -90~90 deg
  - due to **too Large dimension of** obstacle, or **Sparse voxel**

- Curriculum Leaning (by Jeffrey Elman)
  - Firstly, learn at **medium** level (submission code)
  - Learn **hard** level based with same **NN weights**
    - pros: increase success rate **only in hard** environment
    - cons: decrease success rate in medium, and low velocity in both environment



Vision Based approach



Method

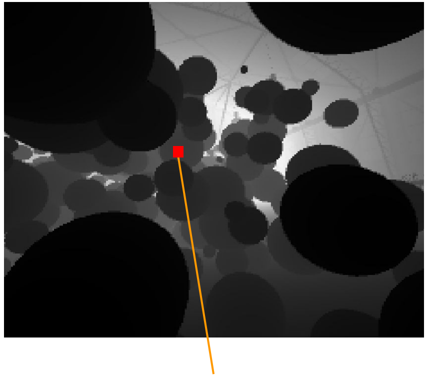
- same policy in state-based
- Make voxel by depth image

Results

goal rate: 6/10 (medium)

Problems

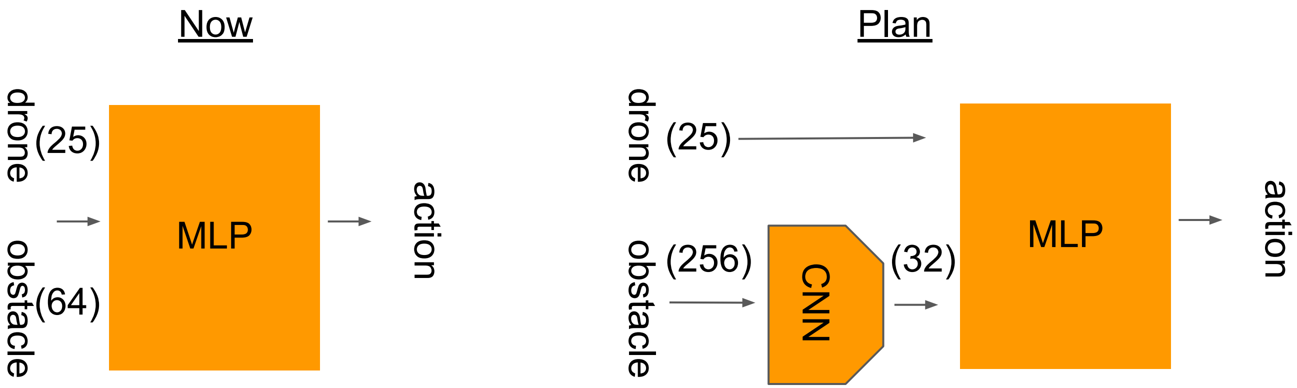
- affect ground in depth sensor
  - quadrotor assume ground as obstacle
  - drones rise
- depth image lack necessary information for voxel production
  - Increase FOV ->
    - Worse performance
    - Worse of depth data in quadrotor direction



depth pick up based on (θ,φ)

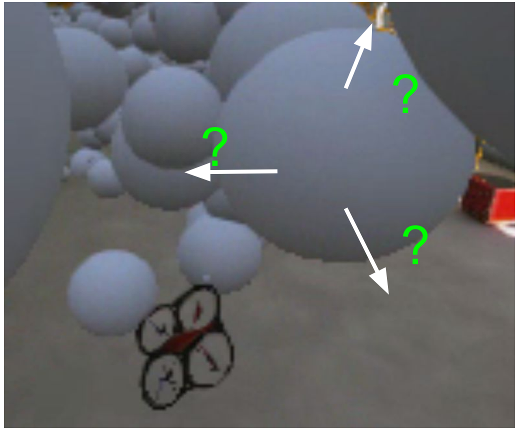
Future works

- Compress Obstacle information by CNN
    - increase input vision dimension, and FOV
        - helpful to avoid obstacle from their side
    - can use voxel position relasionship

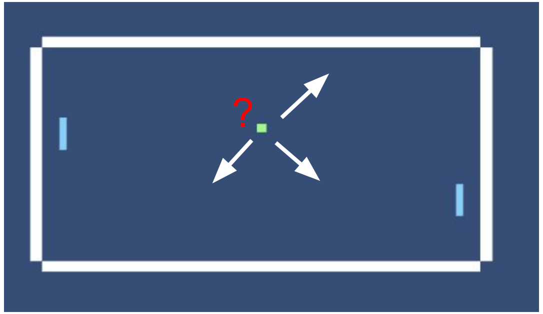


Future works

- Input time-series obstacle information
  - Now, agent don’t know obstacle velocity, and mainly hits moving obstacles
    - POMDP (cf. Pong)
      - harder than MDP
  - Implementing sliding window / RNN



DDC



Pong

Implement to real quadrotor

Implementation difficulty

- Unexplainable, unexpected flight by slight difference
  - 77/100 success on my PC ->1/3 success in the competition
  - 77/100 state-based -> 6/10 vision-based

Implement to real quadrotor

ANYmal

How to solve?

- Get NN based parameter model from real quadrotor for simulator (Jemin Hwangbo et al. Learning Agile and Dynamic Motor Skills for Legged Robots)
- Learning by cheating
  - Learn in many observation space(e.g. obstacles), Reduce observation in real quadrotor
- Dynamic balancing Model (Junhyeok Ahn et al. “Data-Efficient and Safe Learning for Humanoid Locomotion Aided by a Dynamic Balancing Model”)
  - set safety guaranteeing policy design
- Change action space to higher level
  - Eliminate unsafe, unrealistic flight
    - tradeoff of dynamic movement

- Mixed reality framework (Alessanrdo Devo, et al. “Autonomous Single-Image Drone Exploration With Deep Reinforcement Learning and Mixed Reality”)
  - convert real states to simulation engine
- Simulate with noisy observation, time delay

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