MOOS-DAWG'22

Experimental Analysis and Validation of Collision Avoidance Algorithms under High-Traffic Scenarios in Aquatic Environments

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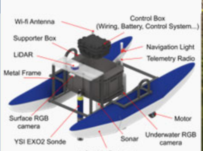
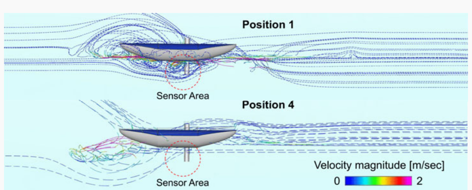
DARTMOUTH

Robotic boat's decision making

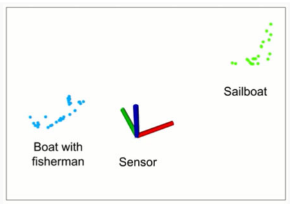
How can I develop and validate a **full pipeline** of a marine decision-making system under **challenging** scenarios?

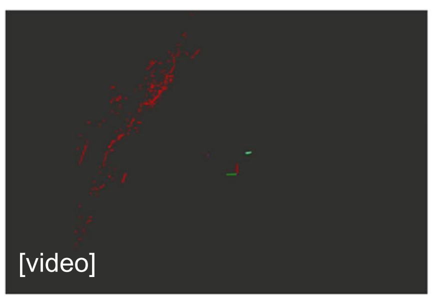
Autonomous Surface Vehicle Optimized Design and Building



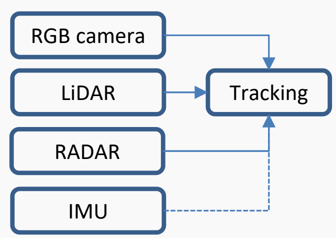


Efficient LiDAR-based In-water Obstacle Detection and Segmentation



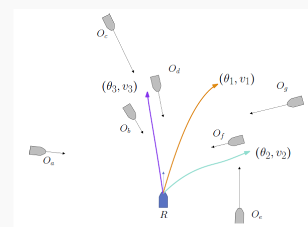


In-water Obstacle Tracking by Multi-Sensor Fusion

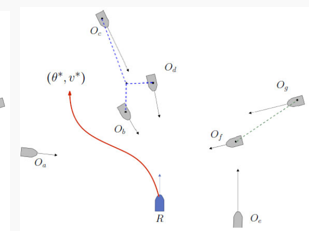


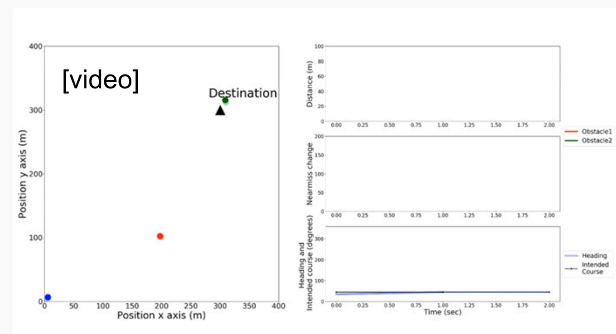
Motion Attribute-based Clustering and Obstacle Avoidance in Heavy Traffic

State-of-the-art approach



Our approach





Robotic Boat for Aquatic Monitoring

Towards a reliable heterogeneous robotic water quality monitoring system: An experimental analysis, Roznere and Jeong, ISER 2020

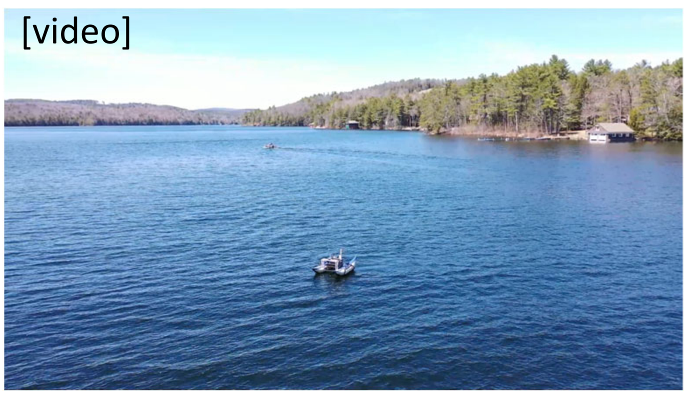
- **Water quality monitoring** in collaboration with biologists, limnologists
- Lake Sunapee, NH. Lake {Auburn, China, Sabattus}, ME

F Lake characteristics, from north to south

Lake or Pond	Trophic state*	Max. depth (m)	WS⁺ Area (km²)
Great	M	21	82.8
China	E	26	69.1
Auburn	M	36	41.2
Sabbatus	E	5	74
Sunapee	O	34	104
Yawgoo	M	11	4.3
Barber	ME	4	1
Wateree	E	24	1542
Murray	E	61	2260

* O = oligotrophic, M = mesotrophic, E = eutrophic, ME = mesoeutrophic

⁺ WS = watershed



Catabot 1 (Generation 1)

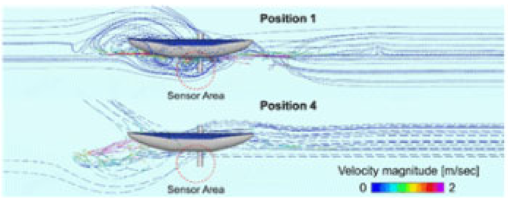
Catabot 2 (Generation 2)

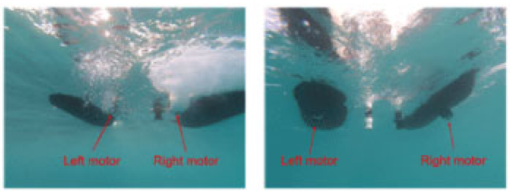
Catabot 3 (Generation 2)

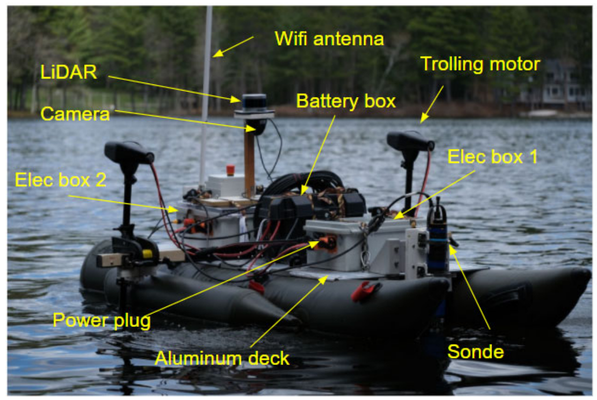
Design, Building of custom ASV Catabot

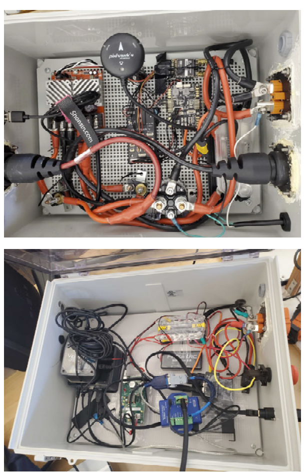
Catabot: Autonomous Surface Vehicle with an Optimized Design for Environmental Monitoring, Jeong et al., OCEANS 2020

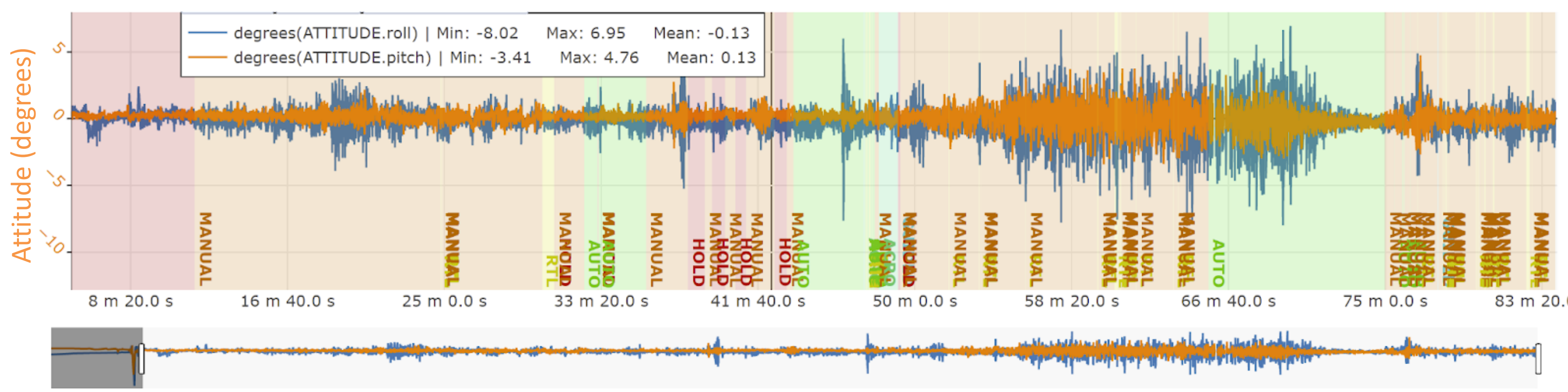
Goal: maneuverability, stable motion and reliable measurements of sensors











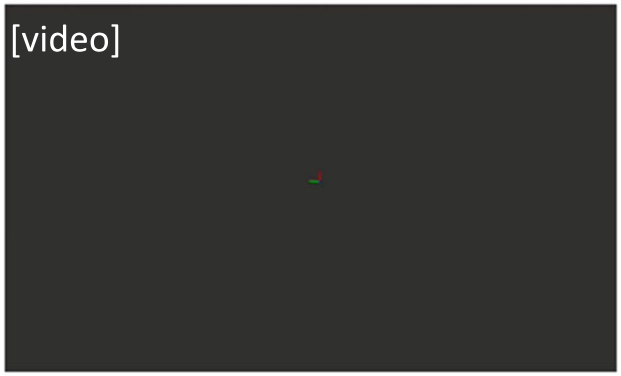
Total cost: about 5,000 USD

In-water Obstacle Segmentation

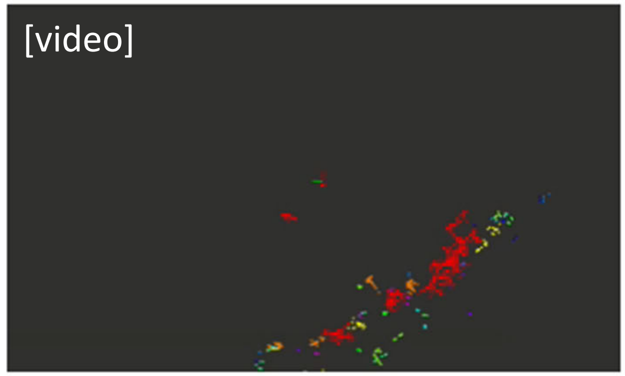
Comparative Result

Efficient LiDAR-based In-water Obstacle Detection and Segmentation
by Autonomous Surface Vehicles in Aquatic Environments, Jeong and Quattrini Li, IROS 2021

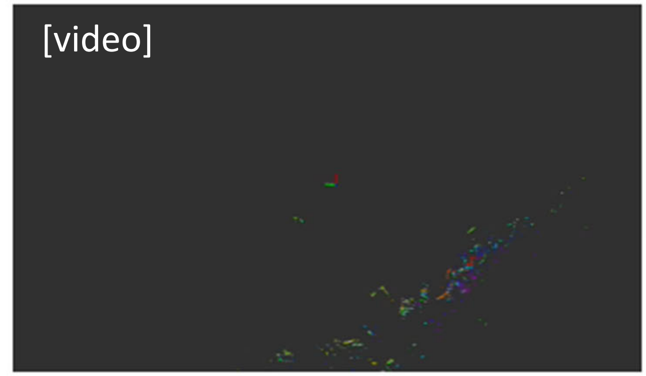
Note: Color label subject to change across frames.



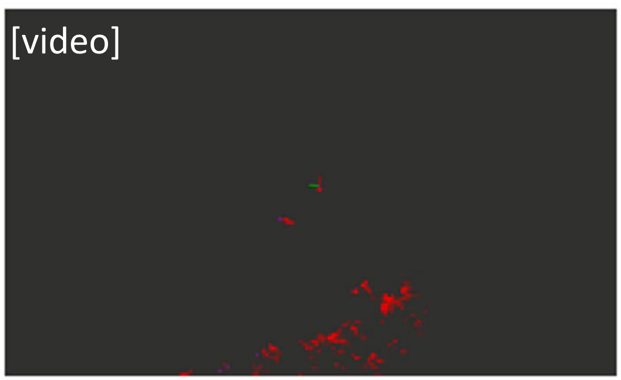
Raw point clouds



EC: Euclidean Clustering (Rusu and Cousins, 2011)

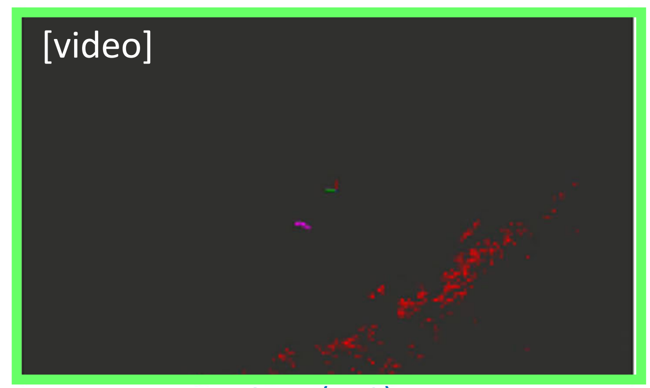


F3D: Fast 3D (Zermas et al., 2017)



SS: SqueezeSeg (Wu et al., 2018)

DC: Depth Clustering (Bogoslavskyi and Stachniss, 2016)



Ours (512)

Problem Statement

- Motion Attribute-based Clustering and Collision Avoidance of Multiple In-water Obstacles by Autonomous Surface Vehicle, Jeong and Quattrini Li, IROS 2022
- Risk vector-based near miss and real-time obstacle avoidance for autonomous surface vehicles, Jeong and Quattrini Li, IROS 2020

“ How can an ASV, operating **complex in-water obstacle** scenarios, assess the situation in a **holistic** way and ensure **non-myopic** collision avoidance?”

Busan, Korea
Recorded by Dartmouth Robotics

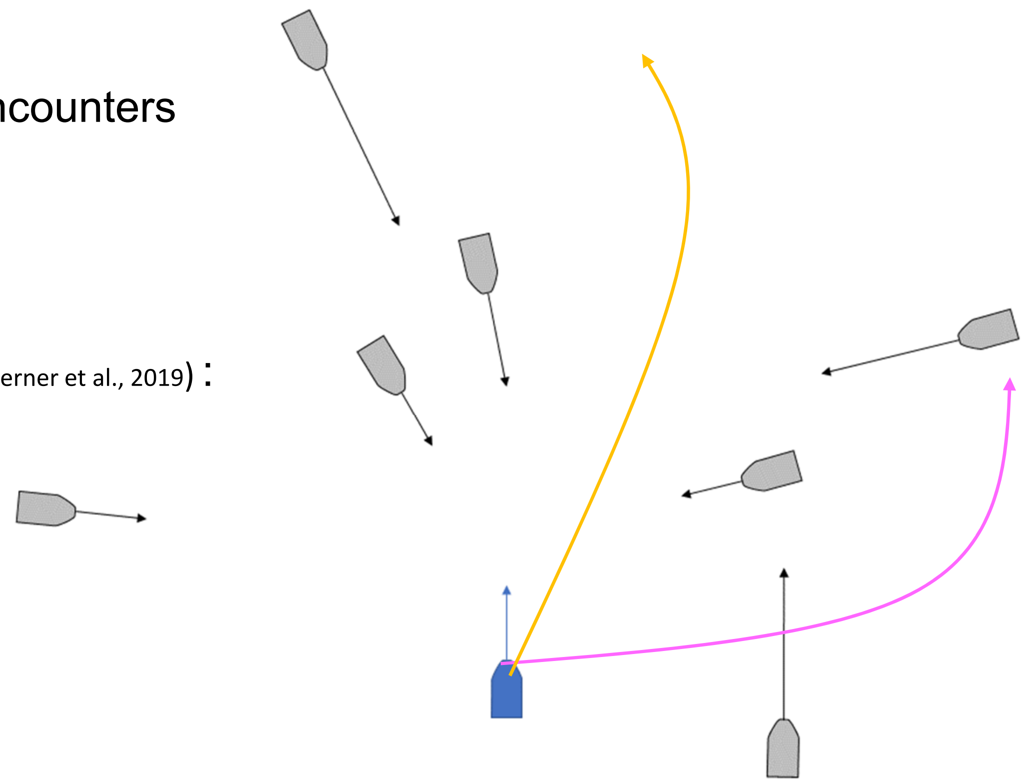
Motivation

Challenges of navigation in high-traffic waters

- Waterways not clearly marked
- COLREGs cover only ***'single-to-single'*** encounters

State-of-the-art methods in multiple encounters

- *sequential, myopic* (Lyu and Yin 2019, Kuwata et al., 2014, Woerner et al., 2019) :
  'role conflicts' *stand-on vs. give-way*



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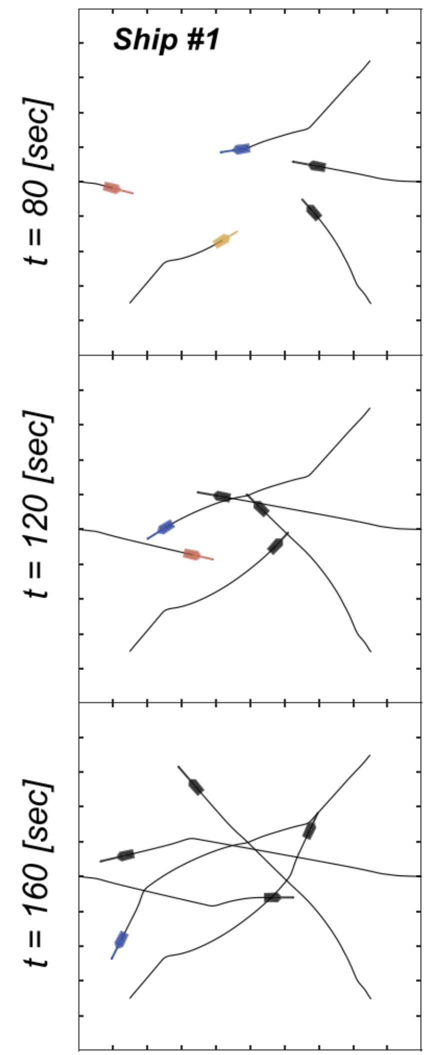
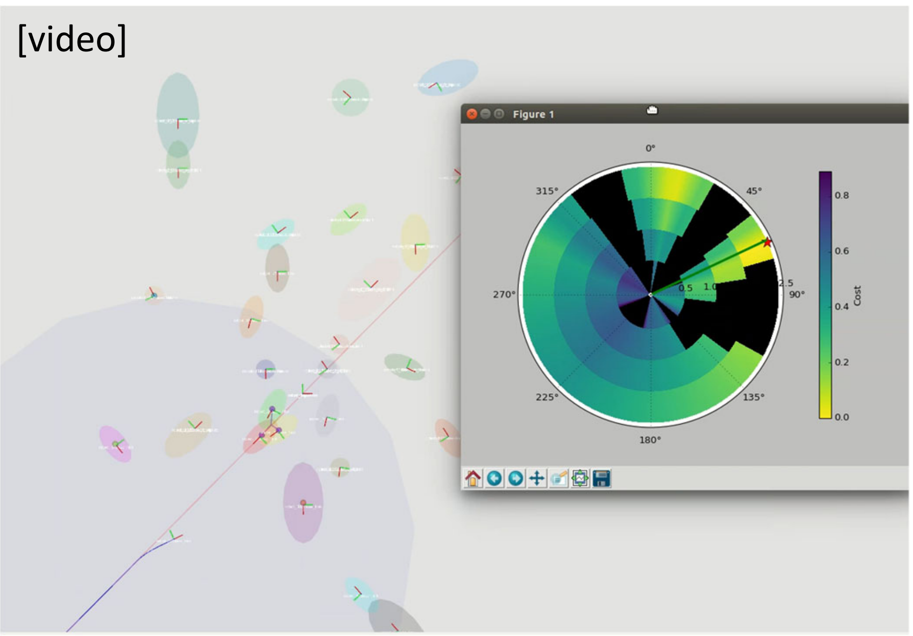
  'role conflicts' *stand-on vs. give-way*
- ***reciprocal*** and ***cooperative*** assumption
  (Cho et al., 2020, Kim et al., 2017):
  not realistic full ***'rule-compliance'***



Cho et al., 2020

Approach Overview

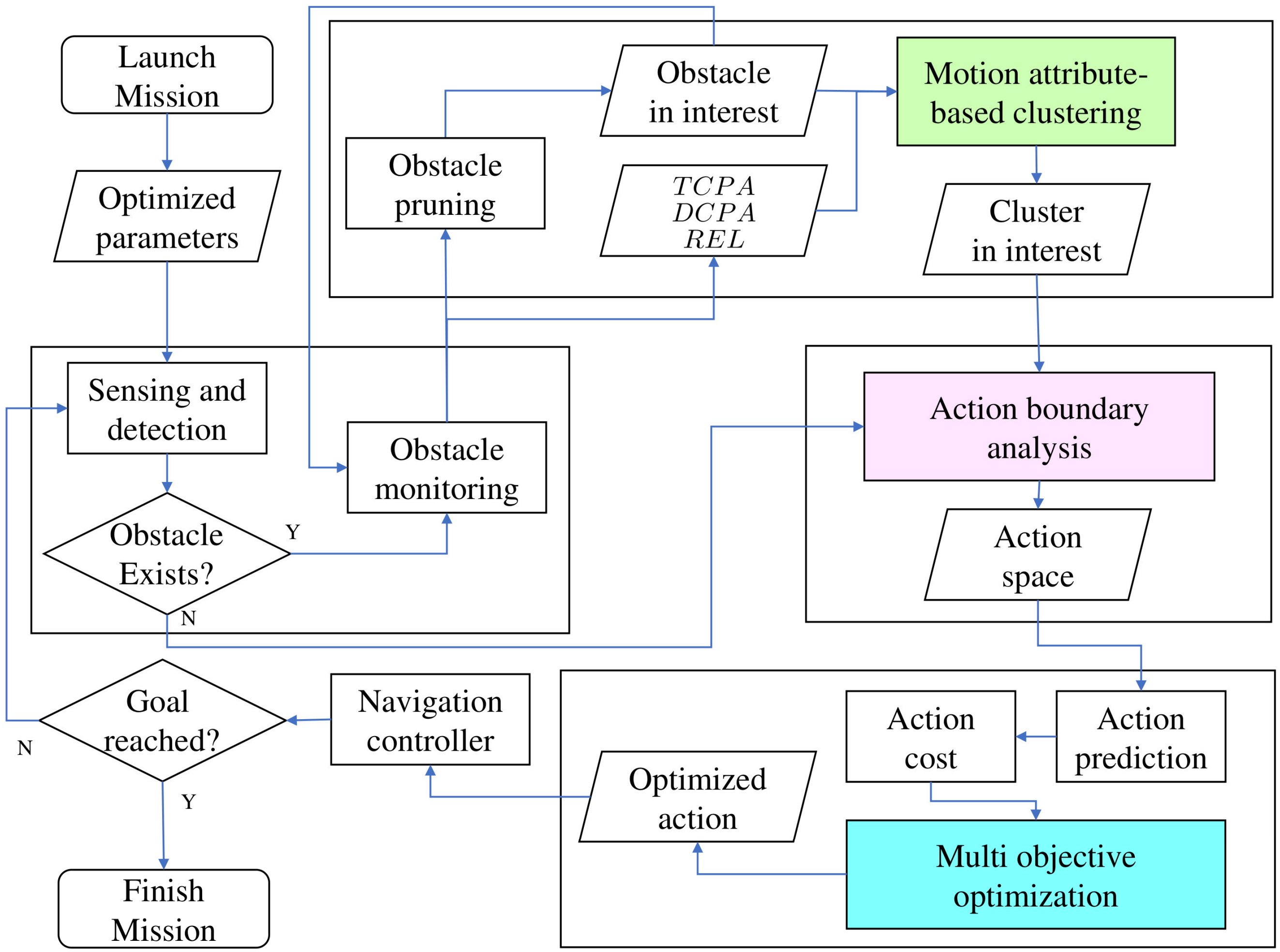
novel real-time non-myopic obstacle avoidance method
for complex in-water obstacle scenarios



- Blue track: controlled ASV
- Environment:30 obstacle case (Singapore Straight)

- Near future **motion attribute-based clustering**
- **Geometric analysis** for feasible action space
- **Multi-objective optimization** for best evasive action

System Architecture

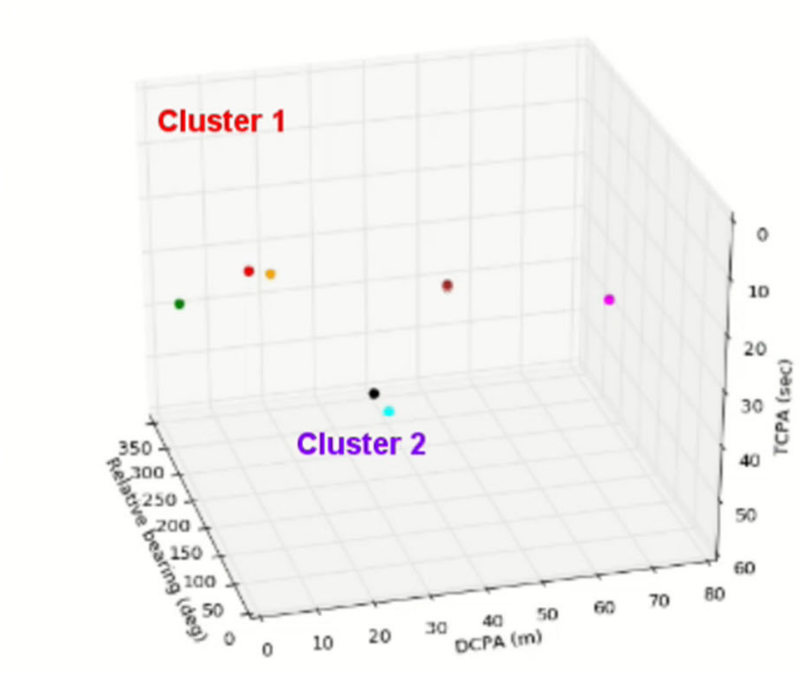


Motion Attributes-based Clustering

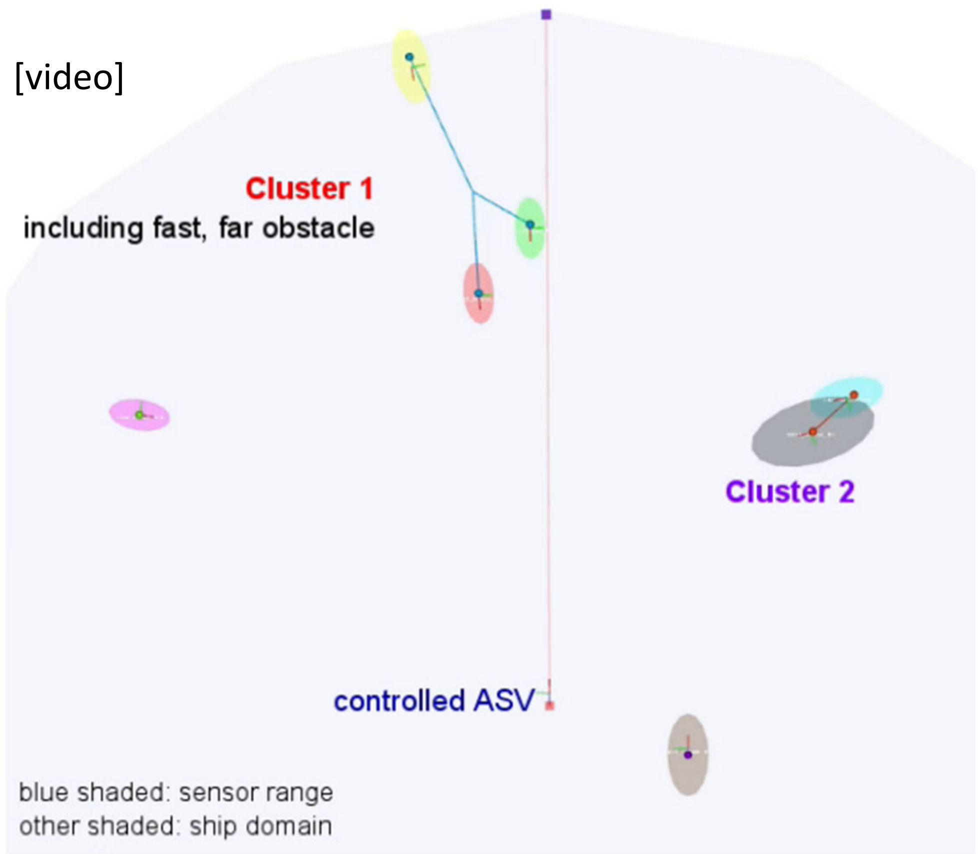
Note: clustering is monitored while ASV is assumed to take no action for clear demonstration.

- Use of **three near future motion attributes** (TCPA, DCPA, relative bearing)
- **Cluster**: a group of obstacles with temporal (s_t), spatial (s_d) and angular similarity (s_a) where obstacle (O_i) meets $T_{monitor^-} \leq TCPA(O_i) \leq T_{monitor^+}$

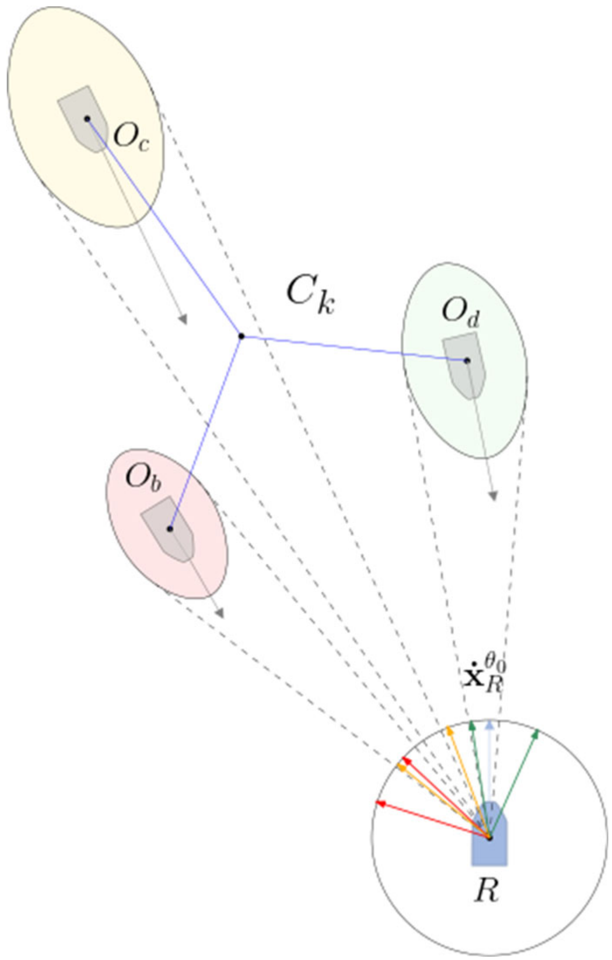
[video]



[video]

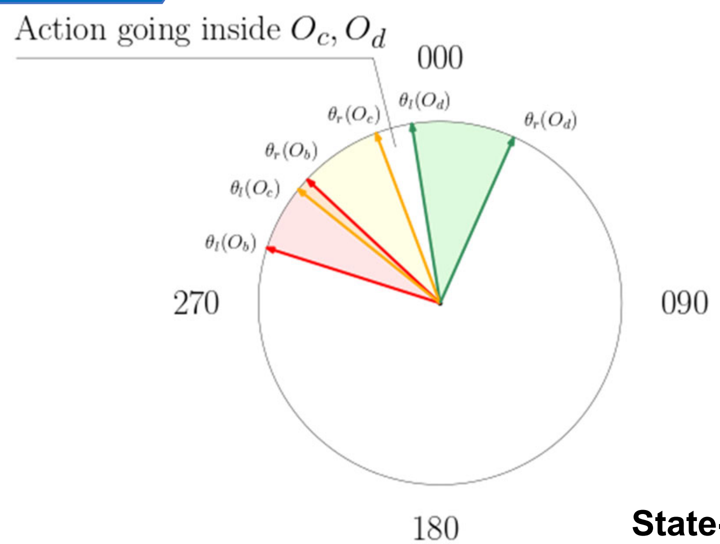


Action Boundary – Multi obstacles

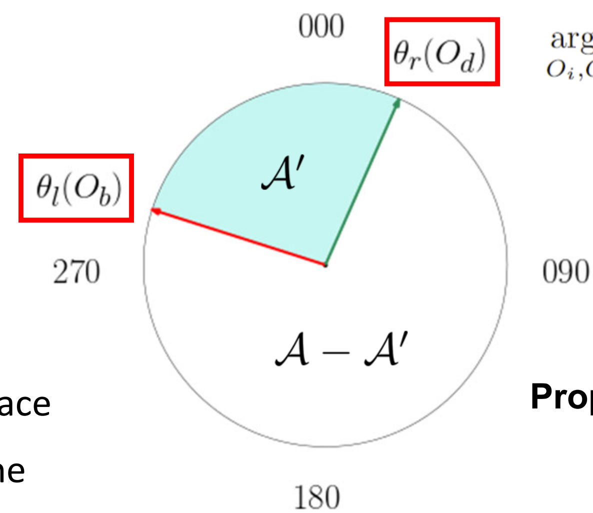


$\mathcal{A}$: action space

$\mathcal{A}'$: no go zone



State-of-the-art approach



$$\underset{O_i, O_j \in C_k}{\arg\max}\ \Theta(\theta_l(O_i), \theta_r(O_j))$$

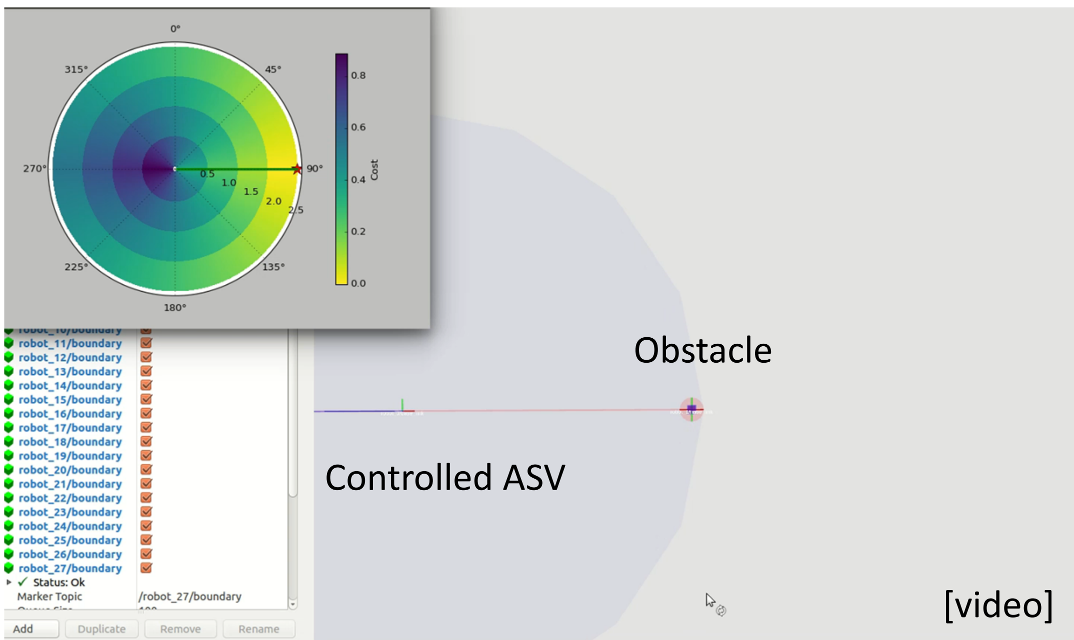
Proposed approach

Multi-Objective Optimization

Pareto Optimal

$$J(\theta, v) = w_f f(\theta) + w_{f_2} f_2(\theta) + w_g g(v) + w_h h(\theta, v)$$

$$(\theta^*, v^*) = \underset{\theta, v \in \mathcal{A} - \mathcal{A}'}{\arg\min} \; J(\theta, v) \qquad s.t. \; w_f \leq w_g, \quad w_{f_2} \leq w_f$$



1. Heading change cost

$$f(\theta) = \frac{|\theta_{wp} - \theta|}{\Delta_{max}(\theta)}$$

2. Speed change cost

$$g(v) = \frac{|v_{target} - v|}{\Delta_{max}(v)}$$

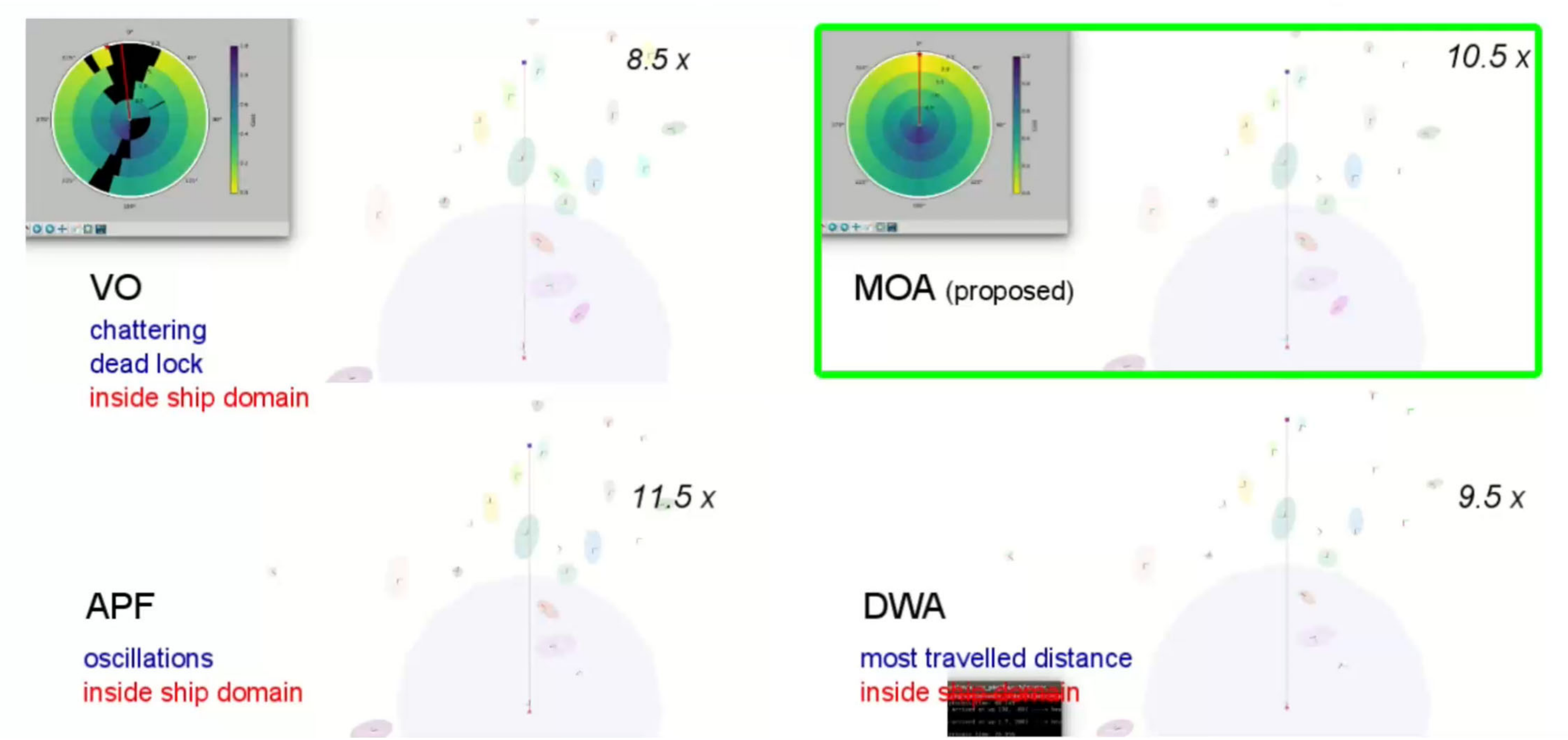
3. Safety level cost

$$h(\theta, v) = \begin{cases} 1 & \text{if} \quad (\tau_{\theta,v} \leq \check{\tau}) \\ 0 & \text{else if} \; (\tau_{\theta,v} \geq \hat{\tau}) \\ \frac{|\hat{\tau} - \tau_{\theta,v}|}{\hat{\tau} - \check{\tau}} & \text{else} \end{cases}$$

Comparative Analysis [video]

MOA: Multi Obstacle Avoidance
VO: Velocity Obstacle
APF: Artificial Potential Field
DWA: Dynamic-Window Approach

- **Monte Carlo simulations**: total **2,000** running in randomized environments
  10, 15, 20, 25, 30 obstacles with random 100 scenario per method



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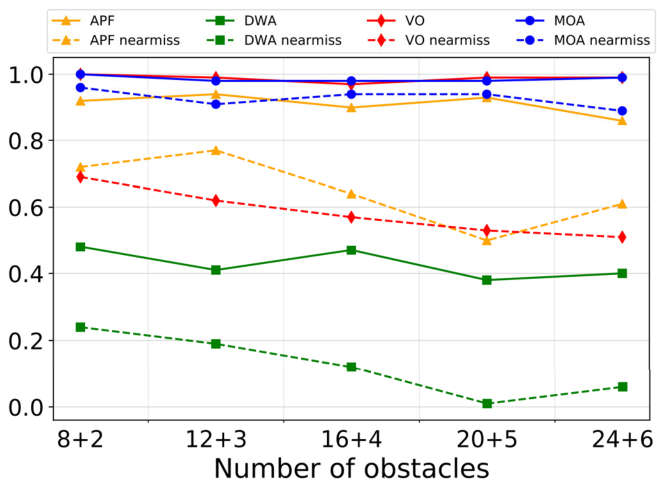
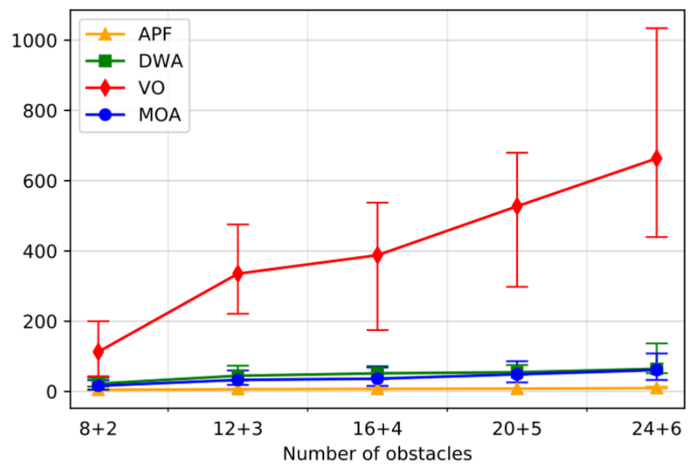
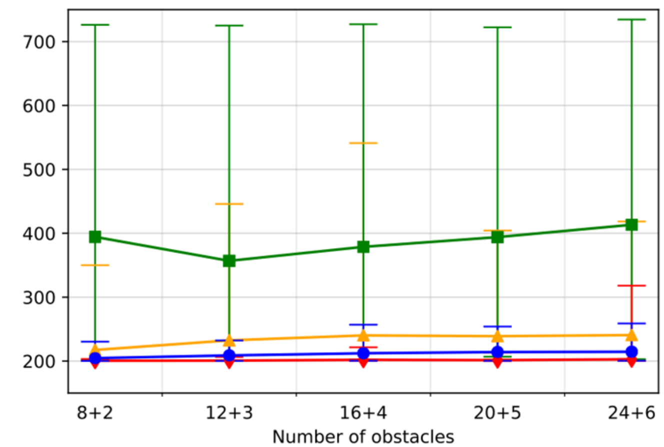
Success rate of navigation



Computation time [ms]



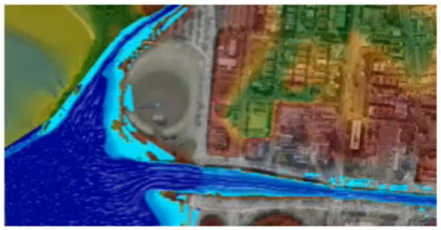
Travelled distance [m]



Real-world like Environment [video]

- Buoyancy, waves, time- and spatial-varying wind (OpenFoam) / water currents (HECRAS)
- Different robotic platform
- Port Alegre, Brazil

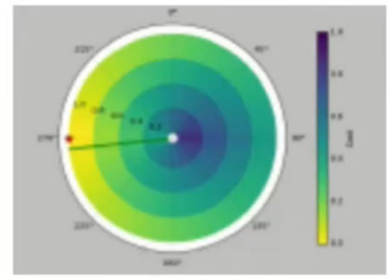
8.9 x



Local disturbances at port Alegre, Brazil

https://github.com/disaster-robotics-proalertas/usv_sim_lsa

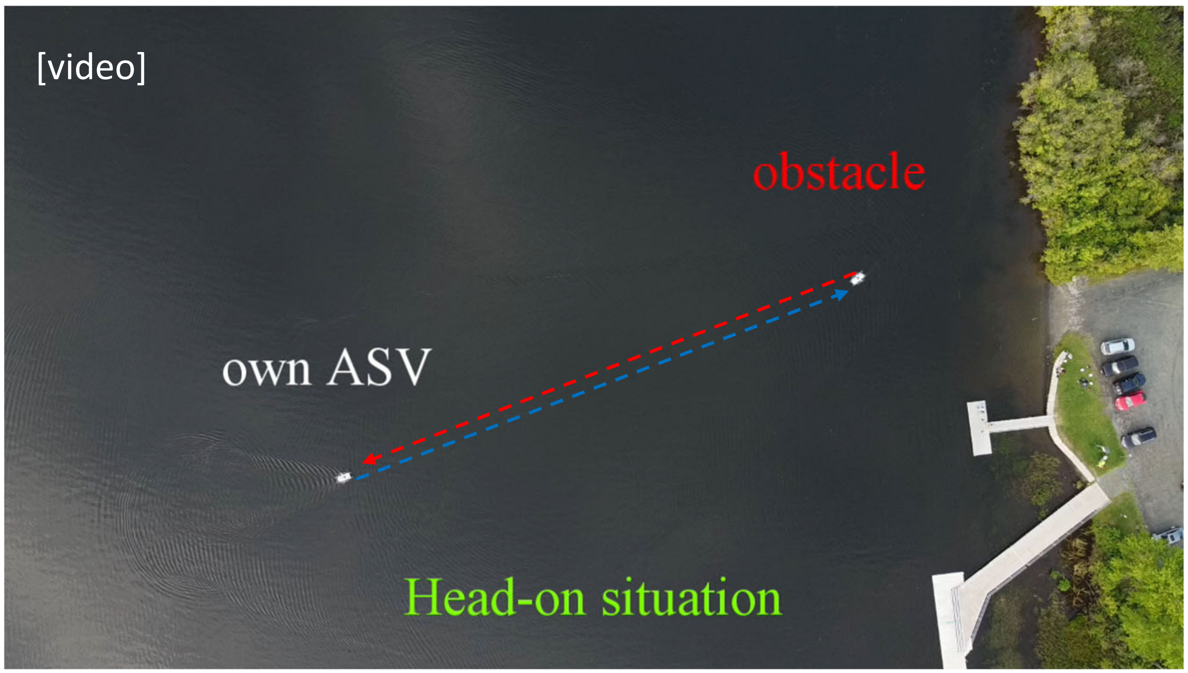
3D motion

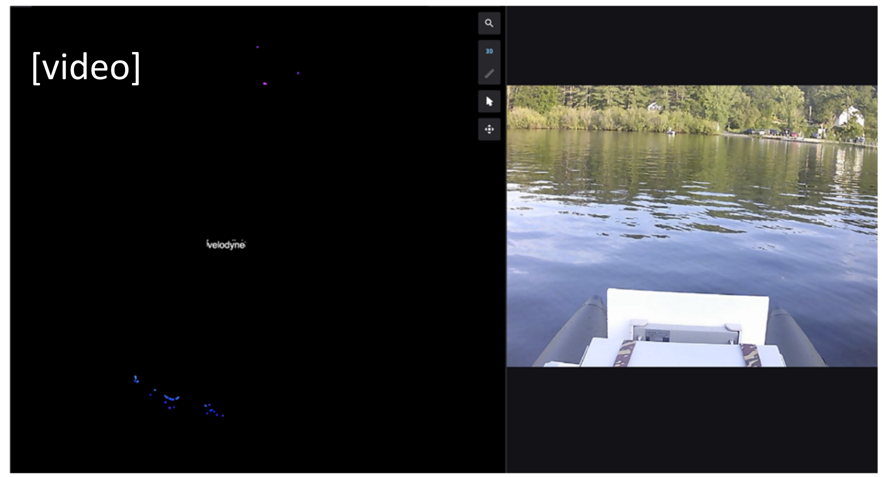


Action space

Field Deployment

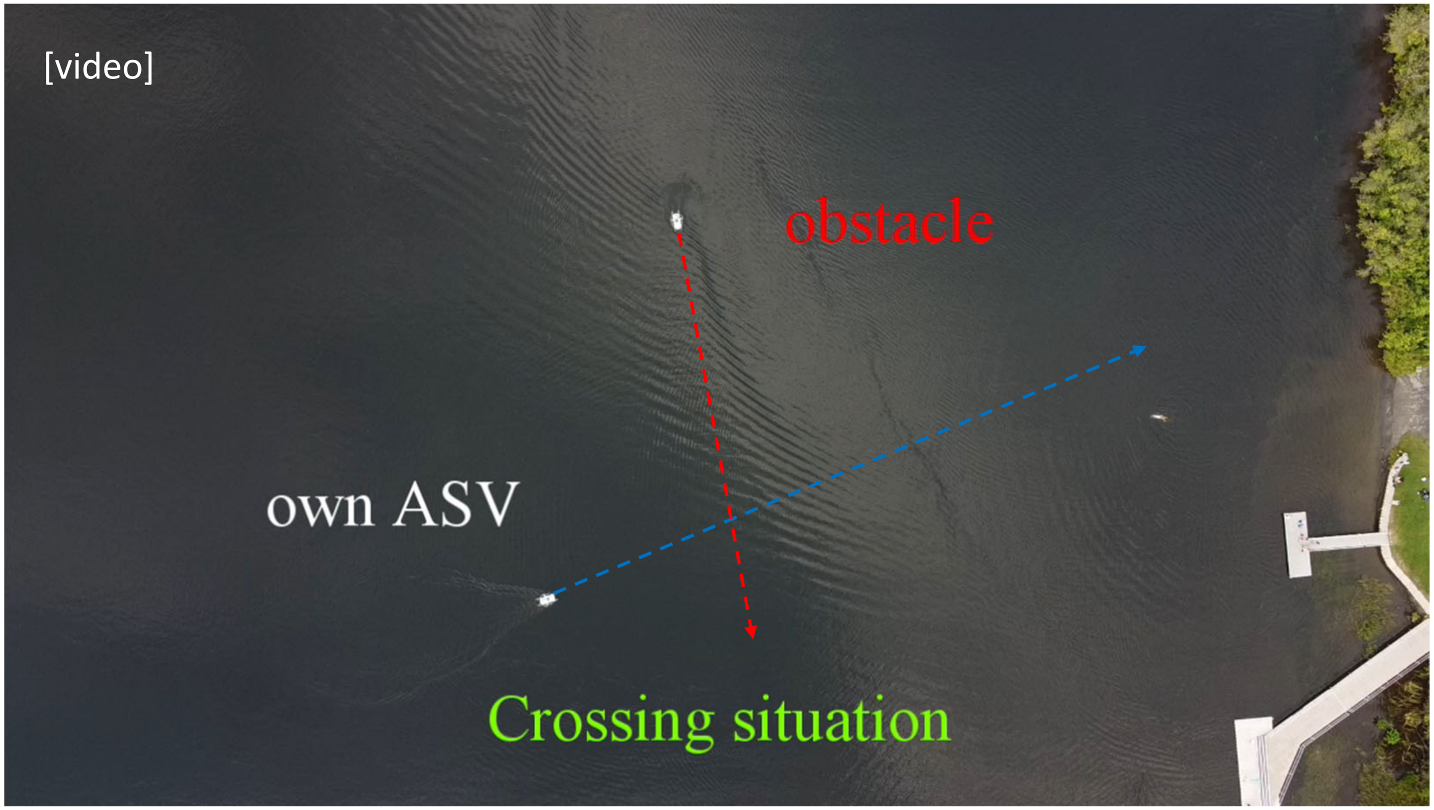
Head-on situation





Field Deployment

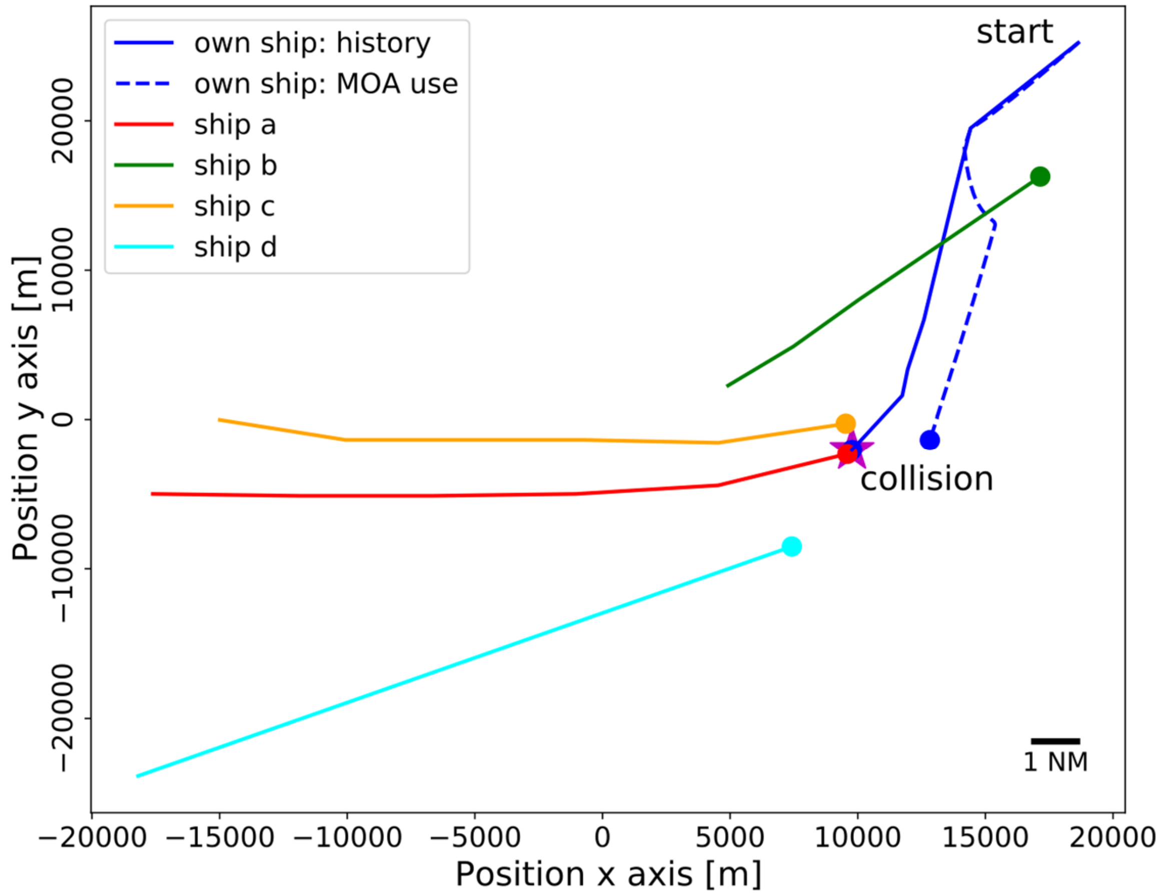
Crossing situation



Real Accident Scenario

USS Fitzgerald and ACX Crystal collision
(Izu Bay Off, Japan, 2017)

ID	length [m]	Heading [°]	Speed [m/s]
R	153.9	220	10.0
ship a	222.6	85	8.8
ship b	267.0	40	6.2
ship c	198.0	95	8.4
ship d	366.4	60	10.0



Conclusion

Significance

- **Motion attributes-based clustering** to identify a group of obstacles
- Non-myopic **holistic avoidance** method for multiple obstacles
- A **real-time** evasive action by **multi-objective optimization**
- Experimental evaluation and comparison under **simulated** configurations and scenarios and **real-world** platform

Future work

- Comparative tests including **MOOS IvP, ROS** navigation stack, etc.
- Connection with global path planning
- Dynamic model constraints and uncertainty
- Towards full pipeline: obstacle detection, tracking, avoidance

Thank you !

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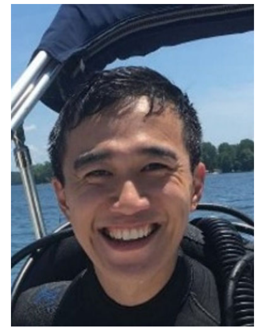

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R-Lab website

https://github.com/dartmouthrobotics

R-Lab github