Revolutionizing Water Quality Monitoring: Autonomous Surface Vehicles and Artificial Intelligence Integration

DARTMOUTH

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Introduction

Monitoring water quality in inland waters is essential for identifying pollutant sources, discerning trends, and evaluating compliance with policy regarding water use. With climate change, it is even more important to conduct thorough monitoring expeditions.

Scientists employ **manual sampling**, high-frequency monitoring **buoys**, and **remote sensing.** However, these techniques inhibit real-time monitoring and studying spatial variations.

Objective

To develop Autonomous Surface Vehicles (ASVs) integrated with artificial intelligence technology, bridging the field of robotics and limnology

Keywords: Autonomous Surface Vehicles; Environmental Monitoring; Marine Autonomy; Decision-making; Water Quality Sampling

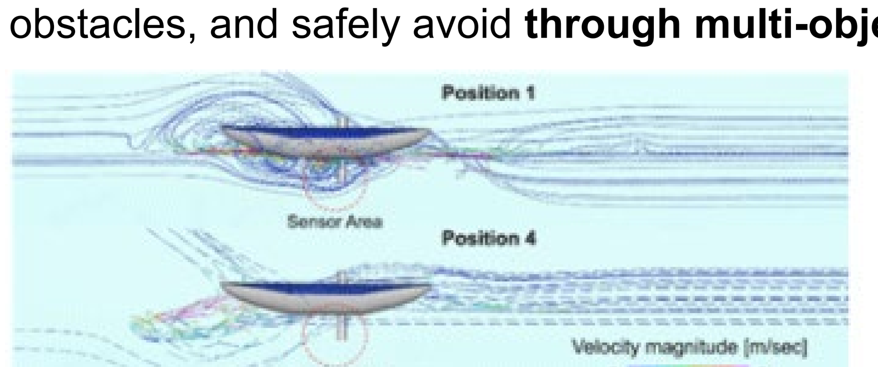
Custom ASV *Catabot* in-water operation

Collaboration between roboticists and limnologists

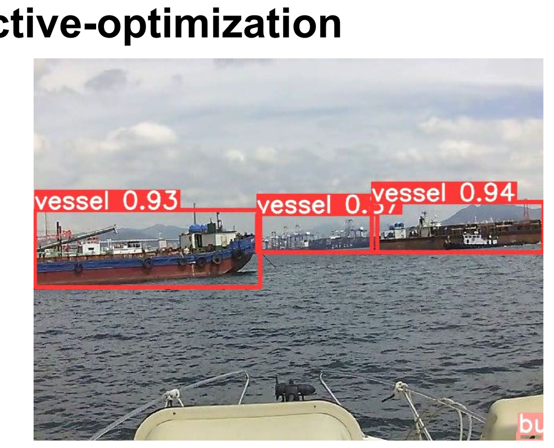
Contributions

Our custom-built ASV, *Catabot*, offers reliable, real-time and repeatable waterbody monitoring solution:

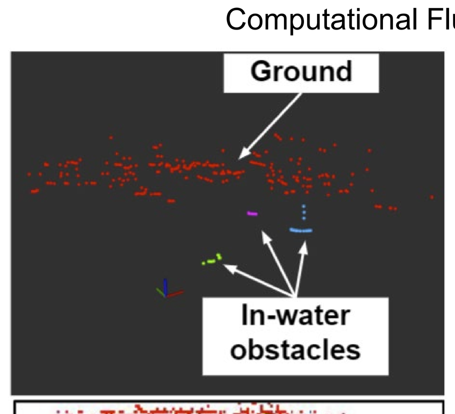
- **High-quality measurements** from a vehicle with motion stability and onboard sensors, including sonar and a water-quality sonde
- **Automated path coverage**, capable of covering 8-10 km over 3 hours
- Expandable into a **multi-robot cooperative team**
- **Marine autonomy** framework that can detect and track multiple in-water obstacles, and safely avoid **through multi-objective-optimization**



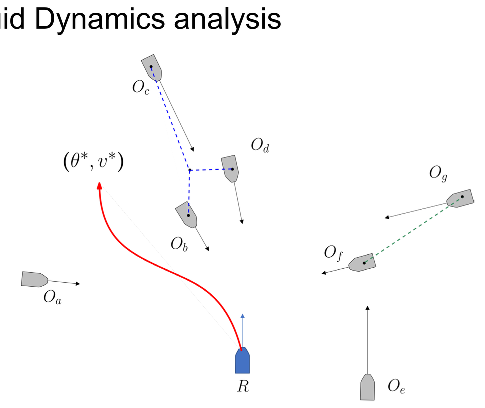
Computational Fluid Dynamics analysis



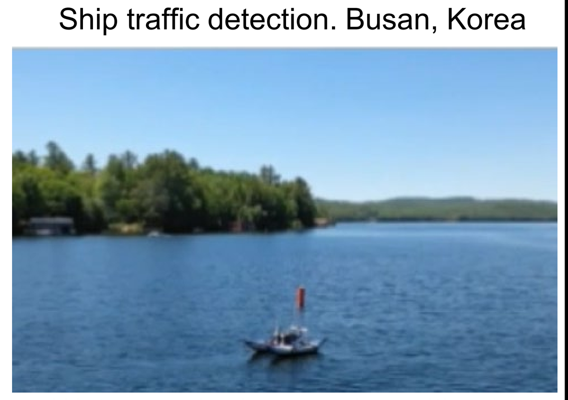
Ship traffic detection. Busan, Korea



Object detection by 3D LIDAR

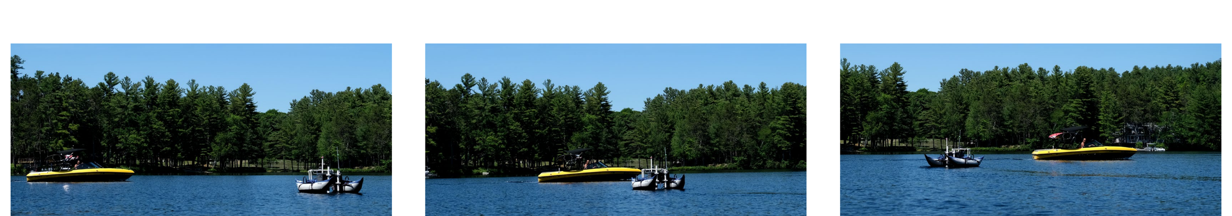


Multiple obstacle avoidance by proposed autonomy approach



Water monitoring together with a buoy at Herrick Cove, Lake Sunapee, NH

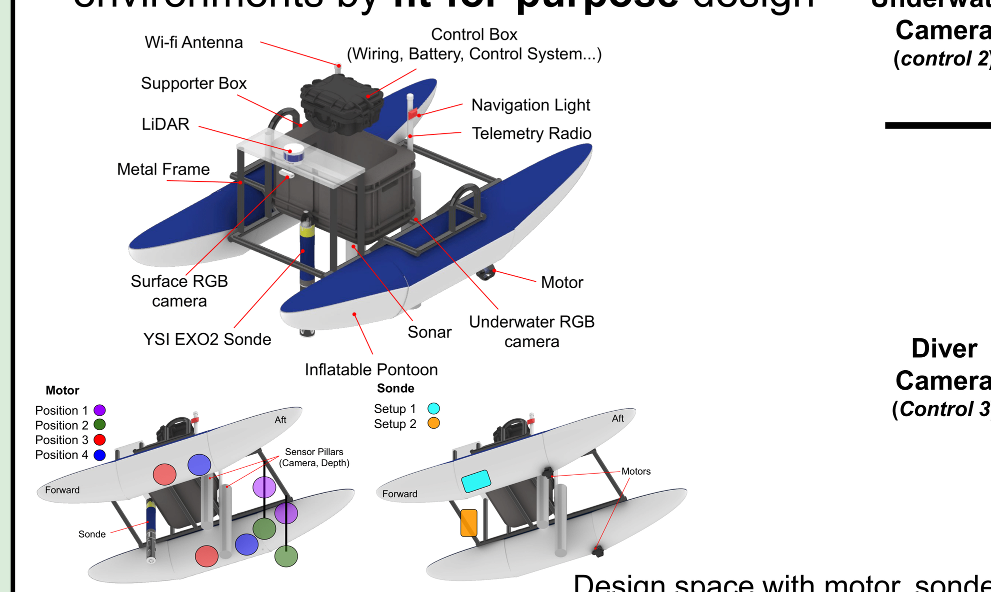
Autonomy in action, Lake Sunapee, NH



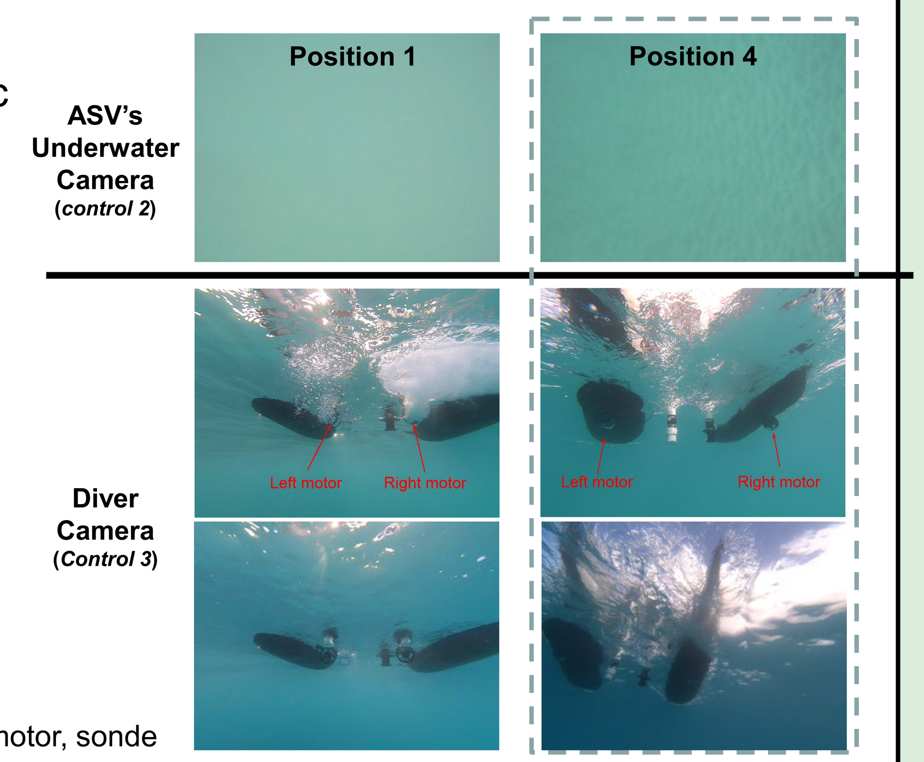
Optimized Design for Environmental Monitoring

Prototype Design Space and Test

- **Reliably** collect measurements in aquatic environments by **fit-for-purpose** design



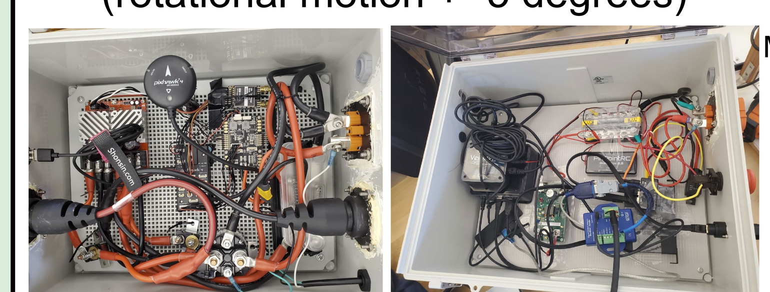
Design space with motor, sonde



Motor wake generation field experiment in Barbados

Improved for Motion Stability

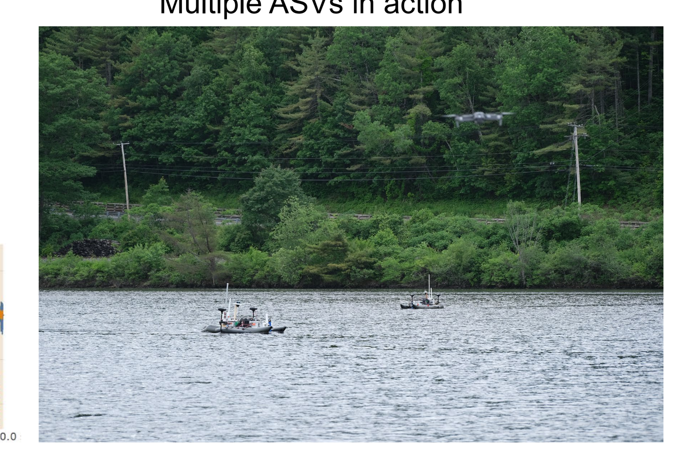
- **Reliably** follow trajectory with **stable** motions (rotational motion +- 5 degrees)



Modular design for fitting

Rotational motion (roll, pitch)

Multiple ASVs in action

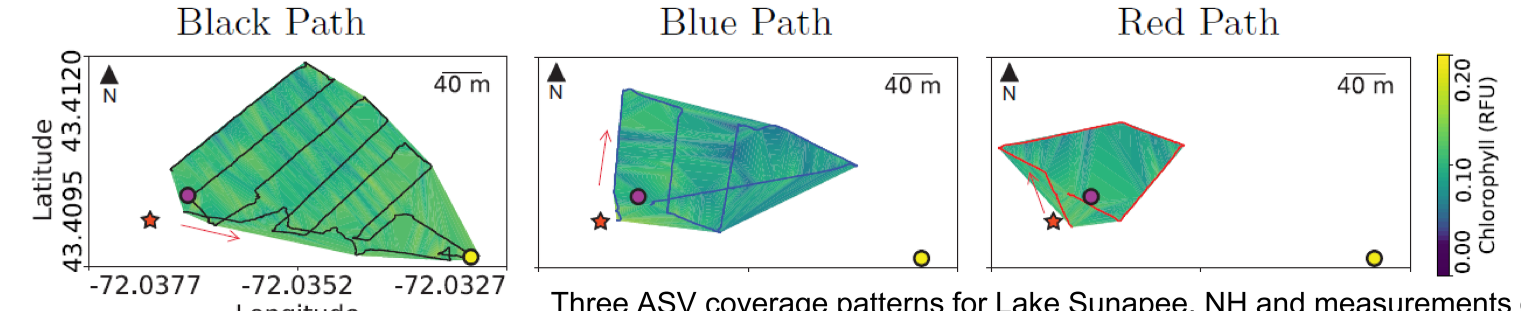


Automated Water Quality Monitoring

Autonomous Path Coverage Example

- Robotic sampling captures **horizontal patterns**

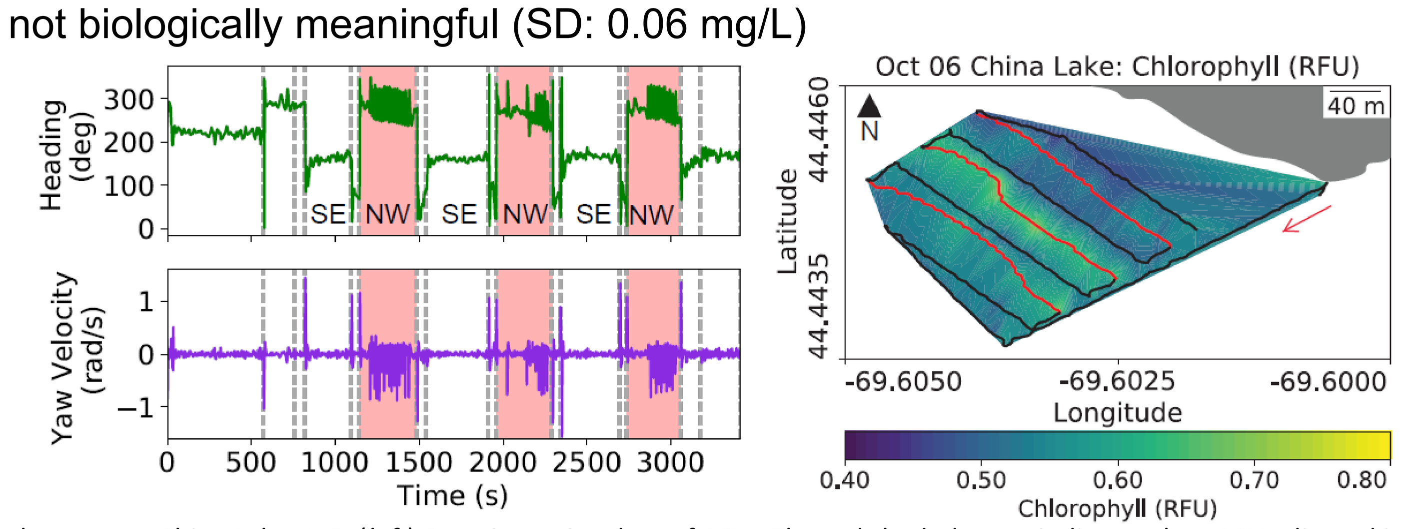
Region	Path	Area (m^2)	Dist. (m)	Time (sec)	Covg. (m^2/sec)	Speed (m/sec)	Mean Chl (RFU ± SD)	Range Chl (RFU)
Sunapee	Black	47215.22	1921	3016	15.65	0.63	0.11 ± 0.01	0.07 - 0.16
	Blue	24232.06	793	1423	17.03	0.56	0.095 ± 0.02	0.05 - 0.16
	Red	14702.29	530	854	17.21	0.62	0.096 ± 0.02	0.06 - 0.13
China		43267.35	2108	3418	12.66	0.62	0.54 ± 0.05	0.44 - 0.71



Three ASV coverage patterns for Lake Sunapee, NH and measurements of surface water chlorophyll fluorescence (RFU, linearly interpolated).

Robot Motion and Sensor Measurement

- **Environmental conditions** can affect ASV's sampling sensitivity and reliability, but not biologically meaningful (SD: 0.06 mg/L)



ASV deployment at China Lake, ME. (*left*) Proprioceptive data of ASV. The red shaded areas indicate when ASV adjusted its heading to counteract external forces while following the NW direction. (*right*) Coverage paths and measurements of surface water chlorophyll (RFU) linearly interpolated across an area of 0.04 km².

Marine Autonomy for Task Performance

Decision-making Module

- Different **rule-compliance** level that enables adaptive analysis
- Modular framework to select a **planner** for collision avoidance

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Find the best action with different objectives:
    best_action(heading*, speed*) = ParetoOptimal
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$$J(\theta, v) = w_f f(\theta) + w_{f_2} f_2(\theta) + w_g g(v) + w_h h(\theta, v)$$

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

1. Heading change cost

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

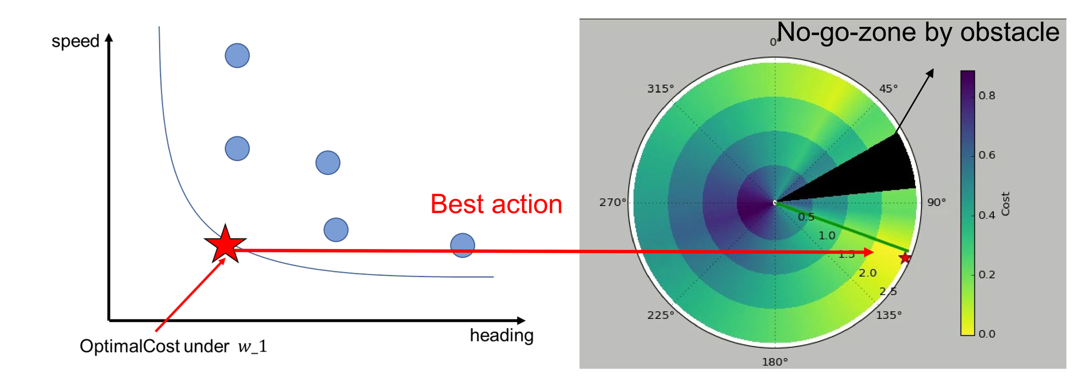
2. Speed change cost

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

3. Safety level cost

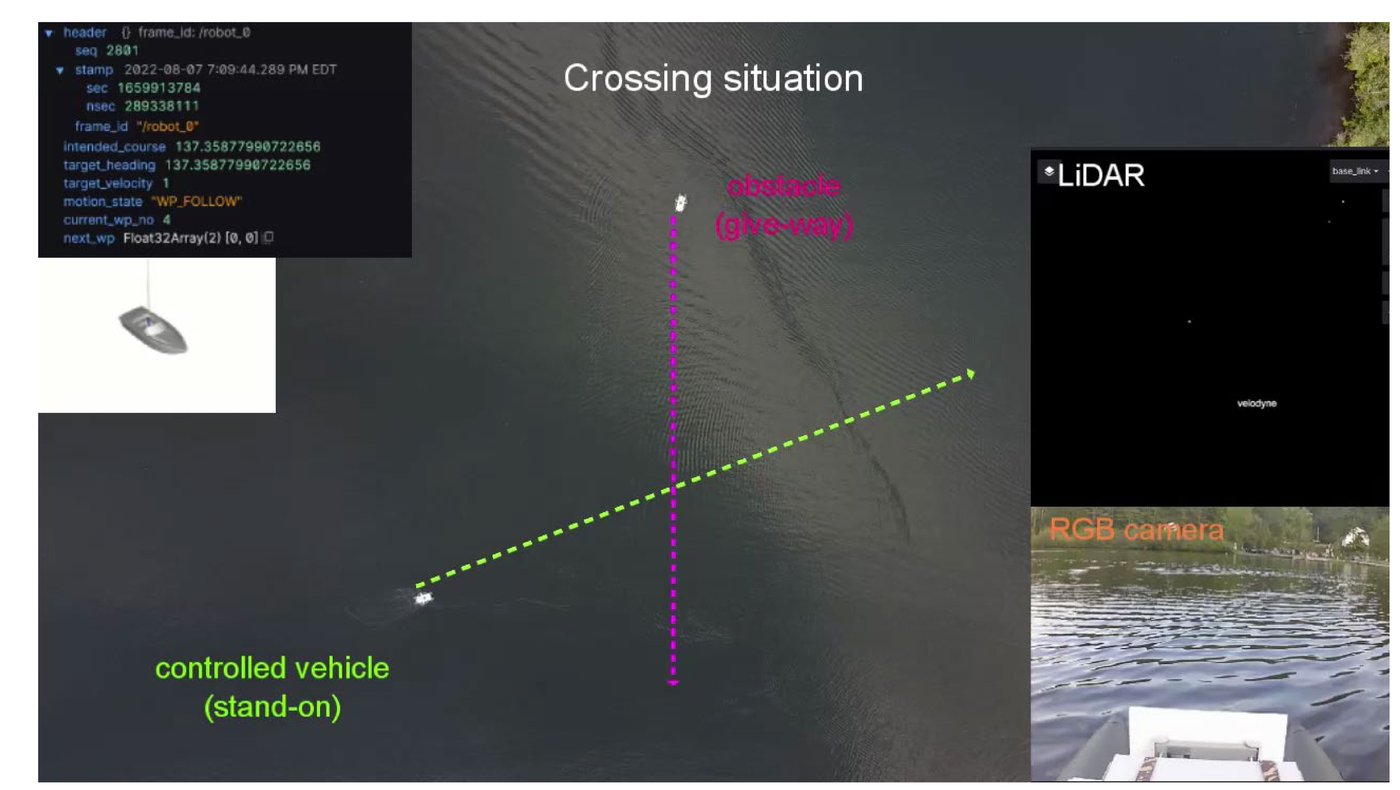
$$h(\theta, v) = \begin{cases} 1 & \text{if} \quad (\tau_{\theta,v} \leq \check{\tau}) \\ 0 & \text{else if} \ (\tau_{\theta,v} \geq \hat{\tau}) \\ \frac{|\hat{\tau} - \tau_{\theta,v}|}{\hat{\tau} - \check{\tau}} & \text{else} \end{cases}$$

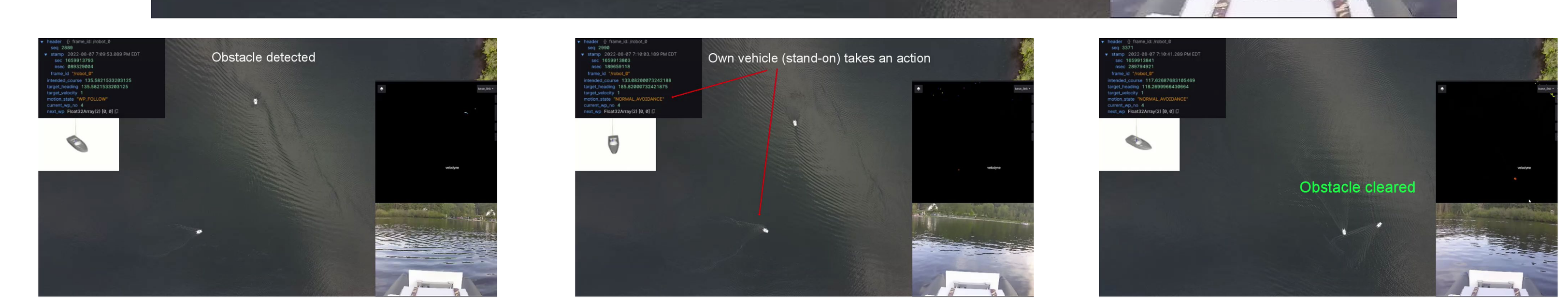
Final desired action: heading and velocity determined by a **Pareto optimization**



Real Robot Deployment

- **Collision avoidance** during environmental monitoring task





Conclusion

Significance
- **ASV** with **AI technology** for reliable, real-time, and stable monitoring
- **High-quality** monitoring, **automated** coverage, and **navigation** system
- Continuously improved based on **robotics** and **limnological** technologies

Future work
- **Low-cost, accessible ASV** with **adaptive** sampling capabilities

References

[1] Jeong et al., Catabot: Autonomous Surface Vehicle with an Optimized Design for Environmental Monitoring, OCEANS 2020
[2] Jeong and Quattrini Li, Efficient LiDAR-based In-water Obstacle Detection and Segmentation by Autonomous Surface Vehicles in Aquatic Environments, IROS 2021
[3] Jeong and Quattrini Li, Motion Attribute-Based Clustering and Collision Avoidance of Multiple In-Water Obstacles by Autonomous Surface Vehicle, IROS, 2022.
[4] Jeong and Quattrini Li, Risk vector-based near miss and real-time obstacle avoidance for autonomous surface vehicles, IROS 2020
[5] Jeong and Quattrini Li, MARCOL: A Maritime Collision Avoidance Decision-making Testbed, AAAI 2023
[6] Roznere and Jeong et al., Towards a Reliable Heterogeneous Robotic Water Quality Monitoring System: An Experimental Analysis, ISER 2021

Acknowledgments

We thank the Eliassen family for our access to the experimental sites.
We also would like to thank NSF for its support to this project (NSF 2144624, OIA1923004, CNS-1919647), Dartmouth Burke Research Initiation Award and NOAA NH SeaGrant.

NSF
Sea Grant