Benefits of real-time object detection for environmental monitoring of marine energy devices

Mr. Paul Murphy¹ Mr. Mitchell Scott^{1,2} Dr. James Joslin^{1,2}

¹MarineSitu ²Applied Physics Laboratory, University of Washington



Background

- Wildlife may be negatively impacted by marine energy devices
 - E.g., collision, disorientation



Background







AMP

AutoAMP

WAMP



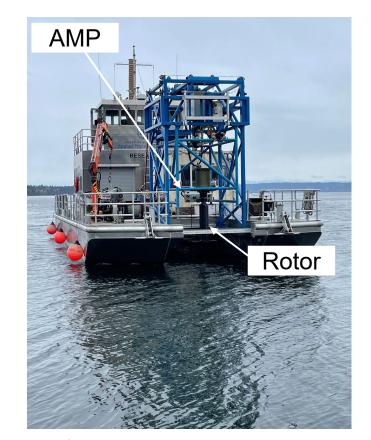
Image credits: Polagye et al. (2020)

Background

- Wildlife may be negatively impacted by marine energy devices
 - E.g., collision, disorientation
- Observing rare events requires persistent monitoring
- Storage and review of large quantities of data is costly and time consuming
- Automated object detection and classification expedites post-processing
- Real-time detection and classification only captures events of interest, reducing data footprint and review time and enabling real-time actions (e.g., momentary illumination)



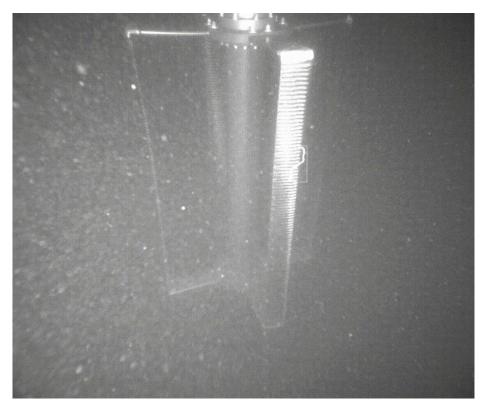
- Deployed LAMP off R/V Russell Davis Light in Agate Pass, WA
- Observed cross-flow turbine with optical and acoustic streams, monitoring for collision or nearcollision events
- Data collection over 7 days (April 18, 2022 April 24, 2022)
- Continuous data collection during daytime.
 Strobes used intermittently at night to avoid biasing animal behavior.
- ML model post-processing only (to date)



R/V light with turbine and LAMP monitoring system



- Targets of interest (small fish, jellyfish, krill, plants) in camera and sonar data hand-labelled and used to train ML model (YOLO-v3) for autonomous object detection
- Model lifecycle: curate and label data, train model, process data, repeat
- Iterated until target accuracy achieved



Fish (?) passes through moving turbine blades without collision. Detections hand labeled.



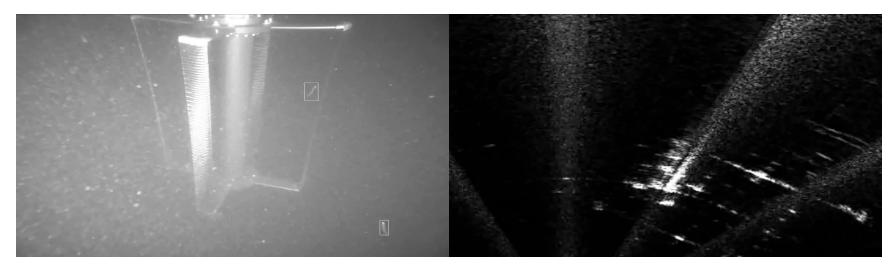


Small fish near turbine. Detections hand labeled.



Small targets near turbine. Detections hand labeled.



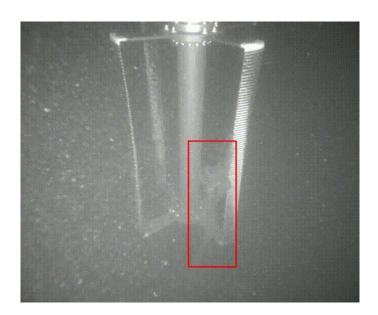


Small fish near turbine. Detections by trained model.

Co-temporal acoustic image (Teledyne BlueView)







Jellyfish collisions. Data played in reverse. Bounding boxes hand drawn.



Accuracy

- Highly dependent on site and model parameters
- 8,467 targets were identified in optical data and hand labelled
- 184,387 targets were identified by the trained ML model
 - False positive rate of all data: **35.1%** (random sample of 100 images)
 - False positive rate of night data only: **7.6%** (random sample of 100 images)
- Accuracy suggests more model tuning is necessary
- High biological productivity, poor visibility
- Artificial lighting at night was superior to natural lighting during day-time



Preparation Time

- Annotation is the most time-consuming component of model preparation
- At **5** seconds per annotation, approximately **12** hours to hand label **8,467** objects
- Labelling services and automated labelling features available to further reduce time and cost, though class designations by domain experts may still be necessary



Data Footprint

- At 125 KB per image (1232 x 1028, 8-bit mono)
 - 875 GB required for ~7 million captured images
 - 21 GB required for 170,969 images containing 184,387 detections*

^{*}biased higher by false positives



Future Work

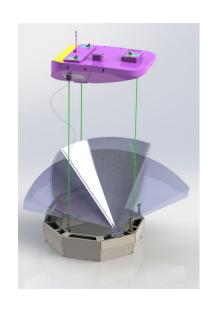
- Further model refinement and development of fish tracking and collision detection
- UW will deploy LAMP and Turbine Lander at MCRL in Sequim Bay
 - Based on prior experience, we expect to see larger fish, fish school, seals, diving birds, detritus, bubble clouds
- ML model will be retrained with newly collected site-specific data and operated in real-time
- As with prior AMP deployments, detection events will trigger actions
 - Data stored in buffers will be written to disk
 - LED lighting will provide momentary exposure synced illumination



LAMP and 3G-AMP Support



LAMP at Marine and Coastal Research Laboratory (MCRL, PNNL)



3G-AMP integration with Oscilla Triton-C at Wave Energy Test Site (WETS)



ORPC RivGen Real-Time Detection

- MarineSitu supporting monitoring of ORPC RivGen turbines with camera systems and software
- Currently recording at 16.67% duty cycle
- With support from TEAMER, MarineSitu is preparing a real-time detection model for a trial deployment this Fall
- Work by Courtney et al. (2022) suggests need for automated fish orientation estimation (detection of disorientation) and collision detection



Salmon smolt passing RivGen turbine, Spring 2021 Image credit: Courtney et al. (2022)



Related Projects

- SBIR Phases I and II (Low-Cost, User-Friendly Monitoring Tools for MHK Sites)
 - Continued tech transfer of AMP technology from UW to MarineSitu
 - Research into transferability of machine learning models between sites
 - Novel hardware and software development
 - Web-based data management and visualization platform
- PNNL AMP
- Pursuing projects in fish passage monitoring at traditional hydroelectric dams
 - Current real-time monitoring primarily relies upon human observers



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Citations

- 1. Polagye B, Joslin J, Murphy P, Cotter E, Scott M, Gibbs P, Bassett C, Stewart A. Adaptable Monitoring Package Development and Deployment: Lessons Learned for Integrated Instrumentation at Marine Energy Sites. Journal of Marine Science and Engineering. 2020; 8(8):553. https://doi.org/10.3390/jmse8080553
- 2. Courtney, M.B., Flanigan, A.J., Hostetter, M. and Seitz, A.C. (2022), Characterizing Sockeye Salmon Smolt Interactions with a Hydrokinetic Turbine in the Kvichak River, Alaska. North Am J Fish Manage, 42: 1054-1065. https://doi.org/10.1002/nafm.10806



Questions



Camera and Light Hardware





Camera Control and Acquisition Software



