BENCHMARKING SENSOR FUSION CAPABILITIES OF AN INTEGRATED MONITORING PACKAGE

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1 INTRODUCTION

The collective understanding of the environmental implications for large-scale deployment of marine renewable energy technologies remains incomplete [1]. Filling these gaps requires instrumentation able to detect events that occur rarely, but with high consequence (e.g. collision between a marine mammal and a turbine), as well as events that occur frequently, but may only be biologically significant when considering cumulative exposure (e.g. a marine mammal within an area of elevated noise) [2].

The intelligent Adaptable Monitoring Package (iAMP) is an integrated instrumentation package that combines a suite of instruments for advanced environmental monitoring capabilities [3,4]. The iAMP (shown in Figure 1a) integrates data streams from optical cameras, multibeam sonars, an array of hydrophones, a fish tag detector, and an acoustic Doppler current profiler (ADCP) into a uniform software interface.

The iAMP instruments are selected to provide comprehensive data about the environment around a marine energy device. The hydrophone array is capable of detecting marine mammal vocalizations to a range of several hundred meters (site and animal dependent). There are two multibeam sonar devices: a Kongsberg M3 (500 kHz) and a BlueView M-series (dual frequency, 900 or 2250 kHz). The M3 can operate at up to 150 m range, and the Blueview 2250 kHz head provides higher resolution imaging within a 10 m range. Optical cameras allow for species classification to a range of up to 8 m (site dependent). The ADCP, a Nortek Signature (500 kHz), provides additional environmental context by monitoring the currents and waves at a site.

Drivers for all iAMP instruments are implemented in National Instruments LabView to centrally control instruments and data acquisition. Data from each instrument is stored in a ring buffer (up to 60 seconds of storage). When a target (e.g. fish or marine mammal) is detected or a save event is generated by a duty cycle timer, all ring buffers are written to disk after a fixed time has elapsed. Use of ring buffers, as opposed to beginning recording when a target is detected, ensures that the entire event is captured (e.g., a 60-s buffer might include 10 s of data prior to event detection and 50 s of data following). This also allows time for target detection algorithms to run without generating a backlog of data.

Continuous data acquisition from all iAMP instruments would produce over 250 GB of data per hour, presenting challenges for both data storage and post-

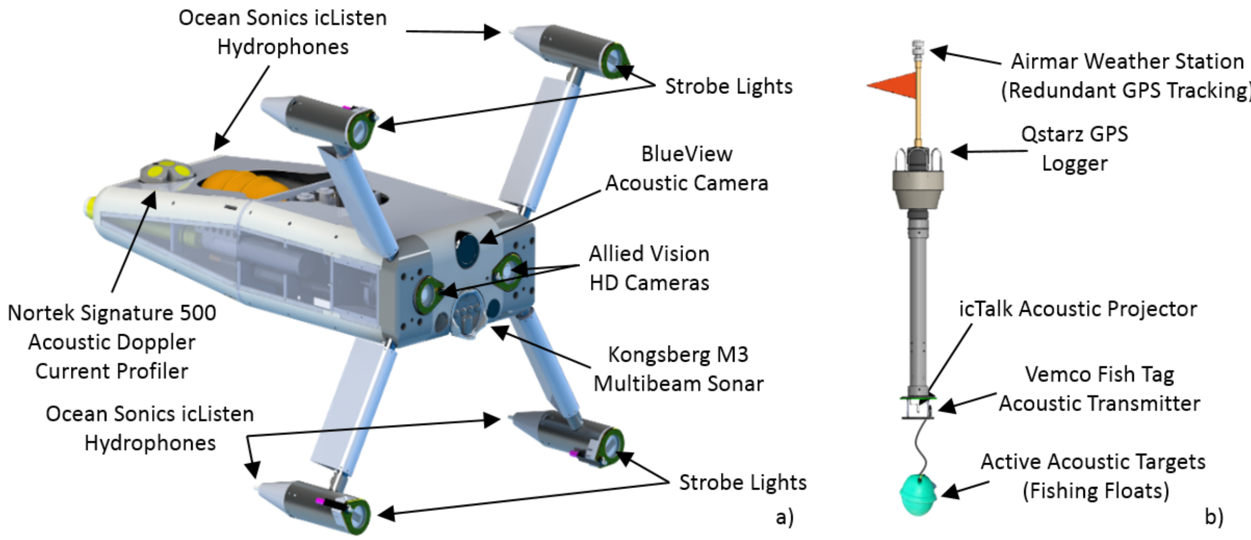

FIGURE 1. A) THE INTELLIGENT ADAPTABLE MONITORING PACKAGE, WITH INSTRUMENTS LABELED. B) SWIFT BUOY AND INSTRUMENTATION USED FOR COOPERATIVE TARGET TESTING

FIGURE 2. iAMP ENDURANCE TESTING SITE AT PNNL MARINE SCIENCES LABORATORY IN SEQUIM, WA

processing. It is preferable for automatic target detection and classification algorithms to limit data acquisition to periods of interest. Detection and tracking of fish and marine mammals on the two multibeam sonar heads (BlueView M900-2250 and Kongsberg M3) will be handled by the Nekton Interaction Monitoring System (NIMS), software developed in collaboration between the Pacific Northwest National Laboratory (PNNL) and the University of Washington. Marine mammal vocalizations are detected by the hydrophone array, and will be classified in PAMGuard (`http://www.pamguard.org`), an open source software package for passive acoustic monitoring of cetaceans. Development and application of triggering algorithms requires training data to allow the selection of thresholds that limits the number of false positives while still capturing most actual events.

2 METHODS

Initial endurance testing of the iAMP is being conducted at the PNNL Marine Sciences Laboratory, in Sequim, WA (see Figure 2). The system is cabled to shore, allowing for data review and software upgrades during endurance testing. Data from all iAMP sensors are collected on a 2% duty cycle (15 seconds every 15 minutes) to test software reliability and collect sample data of opportunistic targets (e.g. fish and marine mammals) passing though the iAMP field of view. Additionally, cooperative targets are moved through the iAMP field of view. These data sets provide training and verification cases for automatic detection algorithms (NIMS, PAMGuard).

Two types of cooperative targets have been used. The Millennium Falcon deployment ROV [4] was used for initial confirmation of instrument functionality and to determine the effective ranges of the instruments. A SWIFT drifter [5] (shown in Figure 1b) was also drifted through the iAMP field of view supporting acoustic targets detectable by the multibeam sonar, an acoustic projector (OceanSonics icTalk) and a VEMCO fish tag to benchmark target detection capabilities of the hydrophone array. The SWIFT drifter was also equipped with GPS loggers to compare the trajectory estimated from the iAMP instruments to the true position of the drifter.

3 RESULTS

During the first 2 months of endurance testing (mid-August to mid-October, 2015), several instances of opportunistic targets were identified in data collected on a duty cycle and annotated during manual review for algorithm training. Figure 3 shows detection of fish by

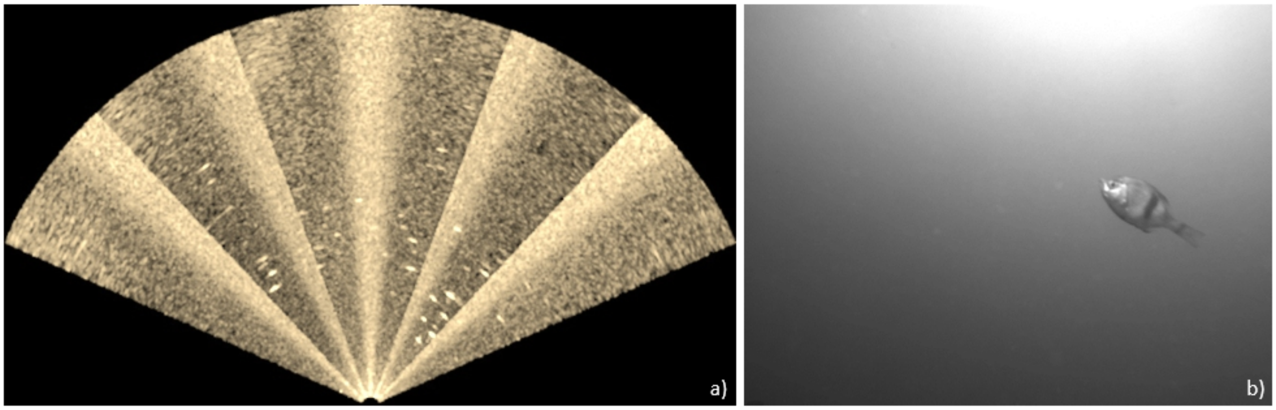

FIGURE 3. A) SCHOOL OF FISH DETECTED ON BLUEVIEW ACOUSTIC CAMERA AND B) FISH DETECTED ON OPTICAL CAMERA.

the BlueView acoustic camera and optical camera.

Cooperative targets proved useful in benchmarking instrument capabilities and expanding the pool of training data for target detection algorithms. Figure 4 shows detection and classification of the VEMCO fish tag and icTalk acoustic projector in PAMGuard, indicated on a spectrogram of hydrophone data. The SWIFT, carrying these acoustic sources, was not detected by the BlueView, due to depth limitations, but was a strong target for the M3. Figure 5 shows the path of a target detected by the M3 and the concurrent GPS trajectory of the SWIFT. The two tracks agree within 3 m. Inconsistencies between the two tracks can be attributed to error in GPS measurements of the SWIFT trajectory and iAMP location, as well as human error in annotating the location of the SWIFT in M3 images.

4 ONGOING AND FUTURE WORK

Not all targets detected by NIMS and PAMGuard will be visible on all instruments. Using the range and heading of a detected target, further regulation of data acquisition can be achieved by only offloading data from instruments that may be able to detect an event. For example, the M3 has a maximum range of 150 meters, and the optical cameras have a range of approximately 8 meters (depending on water clarity). If a target is detected at 40 meter range, it may not be necessary to save high-bandwidth video data of an event that could not be detected by the cameras (though it may be desirable to capture limited optical data to characterize ambient light and turbidity). There is also a high likelihood that patterns will emerge from the collected data. For example, schools of fish might congregate near a device at slack tide every day. In this situation, information about the current speed could allow for situational awareness that dynamically adjusts thresholds for data storage. To detect patterns and rarity of events, a weighted k-nearest neighbors model (kNN) is being

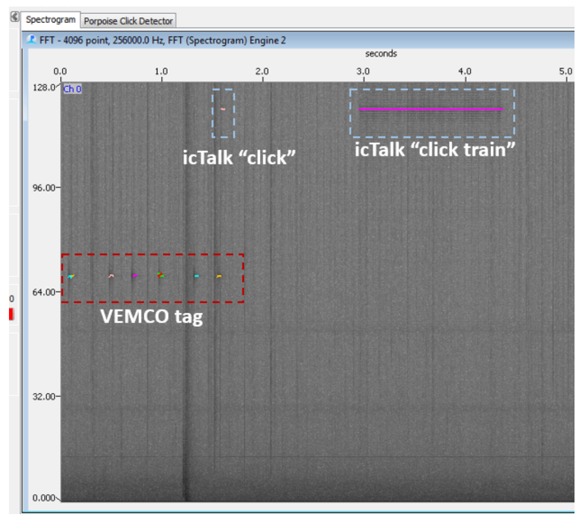

FIGURE 4. ANNOTATED SCREENSHOT OF PAMGUARD OUTPUT, NOTING DETECTION OF ICTALK ACOUSTIC PROJECTOR AND VEMCO FISH TAG. FREQUENCY IS ON THE VERTICAL AXIS AND TIME IS ON THE HORIZONTAL AXIS

implemented for target classification. kNN is a well-studied model for pattern classification, originally introduced by Hart and Cover [6]. Classification of targets will depend on several parameters provided by NIMS and the ADCP: size of the target, speed of the target relative to current speed, target strength, heading and range, and time of day.

In addition, at the beginning of a deployment, the difference between rare and common events may not be known. Marginal examples of specific events could be recorded at the beginning of a deployment, only to find that many stronger examples of that event are detected later in the deployment. Alternatively, due to biological variability, many strong events could occur at the beginning of a deployment, followed by a long period of inactivity. If target acquisition thresholds are

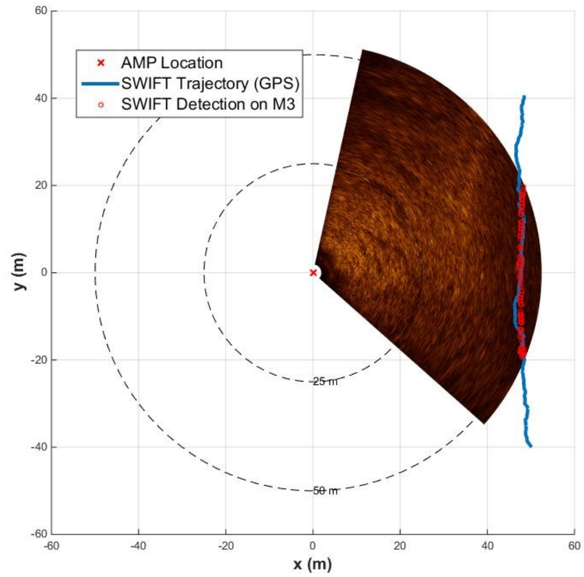

FIGURE 5. SWIFT TRAJECTORY AS DETECTED BY M3 (GREEN) AND GPS LOGGER (RED). M3 FIELD OF VIEW IS SHOWN.

too conservative, this could result in the iAMP failing to maximize useful data capture in favor of waiting for higher priority events that never occur. If thresholds are too permissive, then the risk of a data mortgage [2] for post-processing analysis is increased. For this reason, software is being developed to control dynamic deletion of data based on the priority of a detected event.

5 CONCLUSIONS

Software development and testing of the iAMP has had two major outcomes. First, data acquisition and instrument control software has been tested through a multi-month in-water deployment. Initial data has shown that target detection and hand-off between iAMP instruments is feasible. Second, review of preliminary data has shown the need for further machine learning capabilities to classify detected targets. Future iAMP software development will focus on automatic classification of targets.

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