Autonomous underwater vehicle perception of infrastructure and growth for aquaculture

Erin M. Fischell, Daniel Gomez-Ibanez, Andone Lavery, Tim Stanton, Amy Kukulya

***Abstract*—The use of perception to inform autonomy is important when autonomous underwater vehicles are operating in challenging environments, such as near man-made structures, with unpredictable waves, tides and currents, and in cases where the quality of sensor data are impacted by exact vehicle pose and positioning. An excellent test case for this is in monitoring of offshore macroalgae (seaweed) farms. In New England, these farms consist of complex structures consisting of tensioned longlines that grow sugar kelp. Because of the large extent of these structures and their dynamic behavior, it is a challenge to know *a priori* details of the structure and macroalgae: The exact positioning of longlines changes with time, kelp growth, tide and current direction. As a part of the U.S. Department of Energy's Advanced Research Projects Agency-Energy MARINER program, integrated autonomous underwater vehicle monitoring systems are under development that will incorporate real-time data processing, mapping, and sensor assimilation algorithms for adaptation of sensing missions to environment factors such as true infrastructure locations, currents, and turbidity. These vehicles contain a suite of complementary acoustic, camera, and environmental sensors that will be used in concert with data processing, perception, and autonomy chains to provide high-quality sensor data to users. This paper describes payload design, initial data sets, processing chains, perception and autonomy techniques for the aquaculture mapping and data assimilation problem. Preliminary results from acoustic, camera, and environmental sensing experiments at kelp farm sites in Saco Bay, ME and Buzzards Bay, MA are described, along with future processing and mapping objectives. The preliminary data processing suggests that adaptation will improve vehicle safety and map quality, ultimately providing growers with better actionable data on farm status.**

***Index Terms*—Marine Robotics; Aquaculture;**

I. INTRODUCTION

Robot perception is particularly important in cases of underwater sensing where the underwater robot must respond in real-time or where data must be processed and assimilated to provide an operator with high-level information over a constrained data link. A motivating case for using perception (instead of post-processing of data) is for aquaculture monitoring: the future of ocean farming is offshore, and for economic reasons will require autonomous monitoring[1]. Aquaculture farms may require monitoring of equipment status, growth rates, nutrients, and other factors. The final objective of any such monitoring system is to provide farmers with high-level state such as gear entanglement, growth, and nutrient gradients.

[1]Authors are with the Applied Ocean Physics and Engineering Department at Woods Hole Oceanographic Institution (WHOI), 266 Woods Hole Road, Woods Hole, MA, USA

As a part of the U.S. Department of Energy's Advanced Research Projects Agency–Energy (ARPA-E) MARINER program program, Woods Hole Oceanographic Institution (WHOI) has been developing dedicated payload and autonomy systems for autonomous underwater vehicles (AUVs) that include optic, high-frequency acoustic, and environmental sensors for macroalgae (kelp) monitoring for offshore aquaculture[2]. In farming of sugar kelp in New England, longlines are seeded in the fall with spores that become strands of seaweed and are harvested in early summer[3]. Farmers need information on kelp growth, nutrient gradients, infrastructure health, and surrounding environmental conditions[4]. As non-technical users, they require these data sets in meaningful formats, and need sufficient autonomy and perception in AUV sensing that vehicles can respond to the environment and collect high-quality, actionable information.

This paper describes the sensing system and preliminary sensor fusion, data processing, and perception developed for use in kelp farming systems. First, the context of autonomous monitoring for aquaculture is presented, in particular the ARPA-E MARINER program along with the sensors and vehicles being used for the project. Preliminary data and processing chains are then described, including sonar and camera data processing, along with how these data will be used moving forward for perception-informed autonomy. The sensing systems developed for the ARPA-E MARINER program should be broadly applicable in sensing of aquaculture structures outside of hte macroalgae application, with cross-uses in shellfish, fin fish, and multi-species monitoring.

II. BACKGROUND

To achieve economy of scale required to be a serious competitor in the biofuel market, it is necessary to grow macroalgae (seaweed) on the scale of thousands of hectares offshore [5][2]. This scale will require advanced autonomous sensing for routine survey and quantification of key parameters such as infrastructure health, macroalgae growth rate and distribution variability, impact on the local watercolumn, and nutrient content of the water. Large-scale kelp farming has important fuel sustainability implications, as well as potential for carbon sequestration.

There are several models for scalable offshore seaweed farming, dependent on species and targeted geographic area. In the Northeastern United States, the seaweed grown for food and fuel is sugar kelp (*saccharina latissima*)[6]. The farming technique for growing large amounts of sugar kelp involves arrays of seeded longlines, densely spaced and tensioned, often

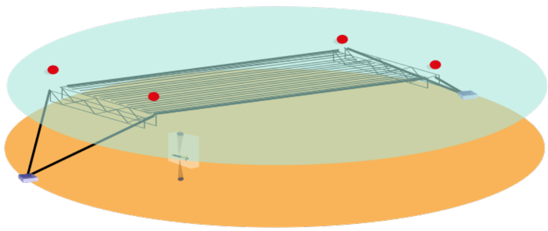

Fig. 1: Sugar kelp farm concept drawing, showing two-anchor system and buoys tensioning seeded longlines. Based on design of farm for ARPA-E MARINER program deployed in Buzzards Bay by Lindell et al.

between submerged steel structures. The longline farm needs to be near enough to the surface for light penetration, but deep enough to not endanger surface vessels. One general configuration is shown in Figure 1: an array of longlines is stretched between two trusses that are in turn tensioned by heavy anchors and surface buoys. The lines between the trusses are seeded, and the neutrally to negatively buoyant sugar kelp grows from the lines. A single array such as the one shown here has dimensions of about 50 m by 200 m, and the kelp grows to lengths of 2 m or more in a season before harvest.

Traditional means of monitoring kelp aquaculture consists of manual inspection. This is not scalable as farms become larger and move offshore- growers need information on structures, growth, and water column properties without having to send boats and people out. Furthermore, modellers and regulators require information on the impact of the farm on surrounding ecology. Both of these needs motivate the development of autonomous sensing technology that would provide growers and others with synoptic, farm-wide data. We are approaching this problem using a combination of autonomous vehicles, sensing technologies, data processing, and mapping.

Previously, other groups have examined the use of robotics and automation for use in aquaculture applications such as fin fish and shellfish farming. Semi-autonomous feed and monitoring systems are now a standard part of industrial fish aquaculture are now common, and include automatic food dispensers, water quality measurements, and are discussed in systems and aquaculture literature e.g. [14] [15] [16]. Detection and tracking of individual fish based on sensor data is also an active research area, e.g. [18] [19] [20]. Examples of mobile robotics are a newer entry into aquaculture- examples include prototypes to feed crayfish in ponds [17] and use of an AUVs for assessing Abalone shellfish stocks [22]. Post-processing is the main means of feature and anomaly identification for these systems. Kelp aquaculture has not historically made use of marine robotics solutions- it has been too small-scale for AUVs or ASVs to be economically viable.

Our contribution is the development of sensor payloads, autonomy, perception, and mapping techniques on autonomous underwater vehicles for use in aquaculture scenarios. This paper presents our initial work towards development of vehicle systems and processing chains for real-time monitoring of growth, infrastructure, and environment at macroalgae farms. While the specifics of this work are geared at kelp aquaculture, the infrastructure and environmental perception aspects are broadly applicable for mapping of fish, shellfish, and seaweed farms in the ocean.

Fig. 2: Snoopy AUV, equipped with broadband echosounder, nitrate sensor, and other environmental/navigation sensors, preparing for deployment in March 2019 at Woods Hole Oceanographic Institution.

III. MARINER AUVs

Two REMUS 100 AUVs, Darter and Snoopy, have been outfitted with specialized sensor payloads for aquaculture. The sensor packages for these vehicles were selected to provide information to macroalgae farmers on nutrients, water column properties, kelp growth, fish/zooplankton distribution, and infrastructure health. Table 1 shows a list of the sensors, uses, and distribution across the vehicles (Darter and Snoopy) used for the MARINER project. AUVs were selected for this project because they are able to complete surveys in variable sea states, provide full-depth water column sensing, and have long-term residence potential moving into the future. The sensor suite was chosen to provide a set of sensing services that are needed by both seaweed growers and modellers.

Both AUVs are equipped with acoustic modems, inertial navigation systems (INS), photosynthetically active radiation (PAR) sensors, and up/down acoustic Doppler current profilers (ADCP). Snoopy is focused on nutrient sensing and acoustics, with an EK80 WBT-Mini broadband, narrow-beam echosounder system[7], Suna V2 Nitrate sensor[8], Optode dissolved oxygen sensor[9], EcoPuck Triplet for biological productivity[10], and a temperature/salinity sensor[11]. The EK80 WBT-mini is a broadband echosounder with a frequency range from 160 kHz-410 kHz that provides detailed quantitative scattering data that can provide the vehicle with estimates of longline locations, seaweed growth, and local biology such as fish and zooplankton. For this project, the data will be used by real-time processing and mapping algorithms to estimate longline locations and kelp growth across the farm. Figure 2 shows the AUV Snoopy prior to deployment in March 2019.

Sensor	Use	Vehicles	Processing
RD Instruments Up/Down ADCP, 1200 kHz	Current estimation, navigation	Snoopy, Darter	Complete
iXbluePhins, Kearfott Inertial Navigation System	Navigation	Snoopy, Darter	Complete
NBOSI CT	Temperature, Salinity	Snoopy, Darter	Complete
Aanderaa Optode O2	Dissolved Oxygen	Snoopy, Darter	Complete
Wetlabs Ecopuck Triplet	Biological productivity	Snoopy, Darter	Complete
LICOR LI-192 PAR	Light levels	Snoopy, Darter	Complete
Simrad EK80 WBT-Mini	Split-beam 200 kHz, single-beam 333 kHz, broadband echosounder	Snoopy	Complete
Sea-Bird Suna V2	Nitrate	Snoopy	Complete
WHOI Custom Kelpcam	360 camera system	Darter	Testing

TABLE I: Sensor configurations for Snoopy and Darter for MARINER project.

Darter, the second AUV, is an optic-focused vehicle, with "Kelpcam", a custom 360 degree camera. This camera will provide growers with automated mapping of farm infrastructure and kelp growth, detection of fish and foreign objects, and on-demand panoramic views for manual inspection of targeted locations. Both AUVs have inertial navigation systems (INS) and Doppler velocity logs (DVL) that minimize navigation error. All algorithms described here assume navigation precision achieved using these systems, and would need to be re-evaluated for vehicles with greater navigation drift.

Preliminary data was collected during two sets of sensing experiments. The first was at the University of New England-managed longline site in Saco Bay, Maine in May 2018, consisting of echosounder and camera data for kelp growing on a single longline. A second set of experiments was conducted in March 2019 at the Woods Hole Oceanographic Institution-managed site in Buzzards Bay, MA. This second set of data included acoustic echo data from a full array of longlines with geometry similar to that shown in Figure 1, watercolumn data on nitrate, biological productivity, temperature, salinity, and currents, and camera data.

IV. Sonar Data Processing

Data from the broadband echosounder on Snoopy consists of frequency-dependent scattering of each point from the vehicle to the surface within the sonar footprint of 7 degrees. The echosounder consists of a split-beam sensor with a center frequency of 200 kHz and a single-beam sensor with a center frequency of 333 kHz. Total frequency range of the system is between 160 kHz and 410 kHz. Calibration of the sonar system based on calibration spheres ensures that all acoustic data will be on the same absolute scale.

This acoustic data can be processed in several ways to extract farm information to aid in sensing and perception. Example data from crossing a longline with kelp growing on it is shown in Figure 3. Water current in this example data is along the line and to the right, and the stipe and blade of the kelp is obvious from the data with higher scattering from stipe and lower scattering from the blade. The longline is identifiable in the acoustic image by strong scattering, and further distinguishable from other features by the frequency characteristics of the scattering. Kelp scattering is related to the kelp biomass in a complex manner that will need to be determined experimentally.

In addition to identification of the longline and kelp scattering, data from the echosounder may be used for detection and classification of fish and zooplankton. While this is not a

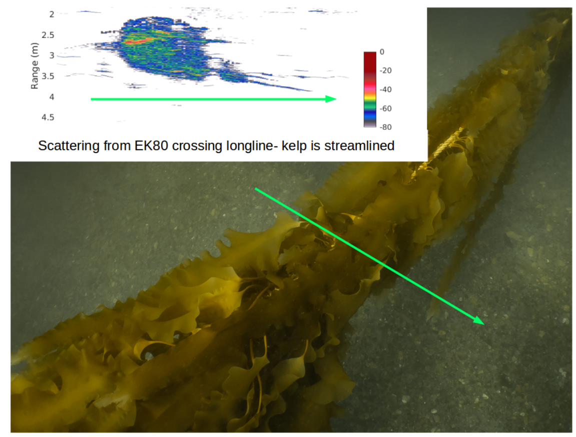

Fig. 3: Bottom: Image of kelp streamlined along longline during Saco Bay experiment. Top: Scattering from kelp plus longline. The green arrow indicates the direction of AUV travel while collecting camera and acoustic images shown in this paper.

primary objective of the MARINER effort, it has the potential to provide information to growers on herbivory and ecology, especially since the kelp farm may attract and serve as a shelter for fish and zooplankton.

A. Infrastructure: Longline Detection and Mapping

To complete first-cut detection and mapping of longline locations, the vehicle will complete a pre-scripted lawnmower pattern underneath the farm site at maximum depth, running approximately perpendicular to lines. An example of the resulting sonar data from Buzzards Bay is shown in Figure 4. This data set is processed using image processing tools to detect longlines in the data– in the case where there is no kelp on the lines, the scattering shows a distinctive "airplane" pattern.

The image processing pipeline that extracts line locations from acoustic data includes a set of steps using existing libraries. First, a black and white image is created from the acoustic range v. time sonar data, with colors set by the median value of the image plus and minus 40 dB for a total range in the image of 80 dB. After threshold-based image formation, the image is Gaussian filtered, converted to a binary image, then dilated using a disk-shaped structural element. Connected components are then identified, with the center of each discrete component associated with a range/time index indicating time for the detection and distance from the AUV sensor to the longline.

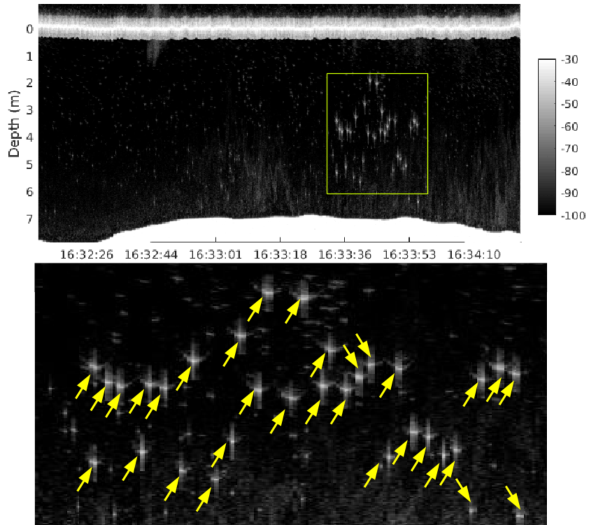

Fig. 4: Example scattering data from kelp longlines without kelp: Buzzards Bay site, March 2019, corrected for AUV depth. AUV is crossing approximately perpendicular to the longlines that make up the farm site. 32 lines are visible in the acoustic data, each marked with a yellow arrow in the zoomed image: each bright "airplane" is one of the 32 longlines at the sugar kelp growing site.

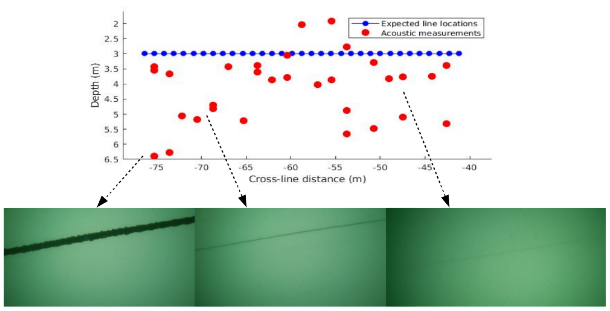

Fig. 5: Estimated depths of longlines versus expected depth from longline array design- a droop of up to 4 m was observed in the acoustics. The acoustic observation was supported by camera data, shown for example line depths below the detection map.

Vehicle internal navigation is used along with sensed distance to the longline and surface to geo-locate line locations on a map. The importance of this process was demonstrated during the March 2019 Buzzards Bay data collection, where some of the longlines were up to 4 m deeper than expected, compromising vehicle safety. The acoustic data was confirmed by up-looking camera data- the AUV passed directly below multiple lines when at a depth of more than 6 m, shown in Figure 5. By first mapping line locations (shown in Figure 6), the AUV can gain situational awareness critical to safe and effective operation.

B. Growth: Acoustic Scattering, Detection and Mapping

The acoustic system can provide information on kelp growth in relation to each longline- example data from crossing a longline with kelp on it in one direction then the other is shown in Figure 7. The broadband echosounder has a seven degree beamwidth, and receives acoustic scattering returns from the intersected area. As the AUV crosses beneath a line,

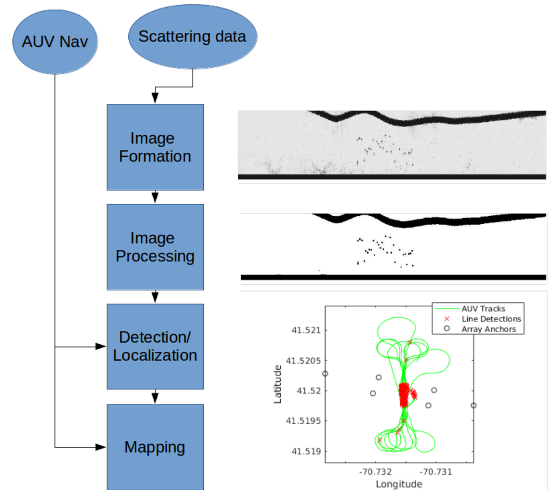

Fig. 6: Longline mapping process. Longlines are detected in the acoustic scattering data, and detections combined with vehicle navigation data to estimate locations. In the future, this process will be done in real time, and more sophisticated mapping techniques used to "connect the dots".

the scattering return ranges are representative of the distance of the kelp from the line[12]. This type of length estimation has been used previously with echosounder systems to measure kelp, e.g. by Blight et al. [13]. In addition to range to the edge of the kelp from the line, the intensity of the scattering from kelp will be mapped across each farm site. The relationship between acoustic echo energy and harvested biomass will be investigated in field experiments. Although attempts will be made to relate the acoustic data to absolute biomass, the variability of energy scattered by the kelp should provide users with a way to identify anomalies in that growth. By repeatedly crossing under and perpendicular to the lines, with paths autonomously selected based on preliminary line mapping, the AUV can get a farm-wide measurement representative of growth.

To isolate the acoustic echoes from the kelp for analysis, image processing is used to mask the area consisting of the kelp "ball" in the echosounder data (Figure 8). This masked area is then used to estimate range from the line to kelp edge from acoustic time of flight, and to estimate the amount of acoustic echo energy due to backscatter from the kelp. The image segmentation process includes converting to black and white, followed by image erosion, reconstructions, dilation, Gaussian filtering and binarization. The binary image is then filtered again to connect nearby areas, and connected areas approximated with ellipses. These ellipses are then used as masks on the acoustic scattering data to estimate the distance of the kelp edge from the line and the total scattering from the sonar footprint when intersecting with the kelp.

V. Camera Data Processing

Kelpcam consists of five cameras arranged in a radial circle plus a sixth forward-facing camera, each with wide-angle lens and dome viewports. Individual camera fields of view overlap, so Kelpcam can capture a nearly-continuous spherical panorama when triggered by AUV mission executive.

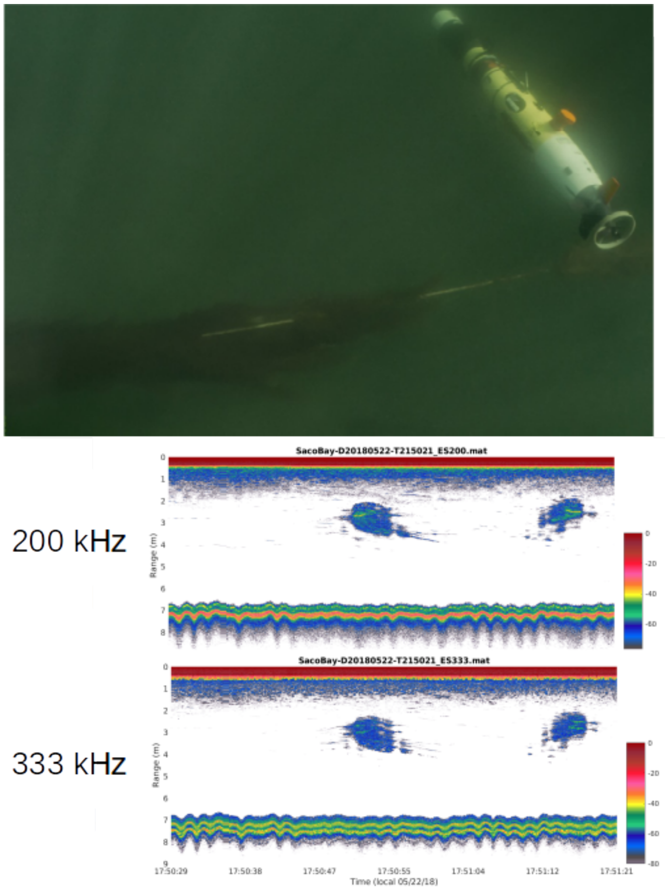

Fig. 7: Acoustic scattering from *Saccharina latissima* during Saco Bay Experiment when AUV crosses the longline. Scattering shown as AUV crosses the longline with kelp on it, then turns around and crosses the longline in the other direction. A "ball" of kelp/line scattering is evident in each sonar image, 200-kHz center-frequency transducer above and 333-kHz center-frequency transducer below. Each blue "ball" shows the acoustic scattering in the relevant frequency band from overlapping kelp streamlining along the kelp line.

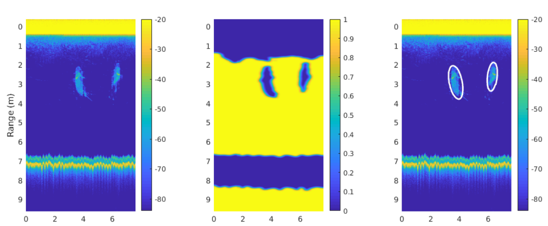

Fig. 8: Isolation of kelp echoes through masking process. Original image shown in the first frame, mask in the second, and ellipse approximation shown in the final frame.

Captured images are combined side-by-side to create a single panoramic view at each vehicle waypoint. This panoramic presentation is useful for human viewing, and allows intuitive inspection of kelp and farm infrastructure, in response to problems detected through the automated farm mapping system.

However, it is not feasible or desirable for a human to review each image. Long-term monitoring can easily capture many thousands of images, and most images are empty of useful information. Instead, images are used as input to several feature detectors: kelp detector, infrastructure detector, and foreign object detector. All image locations, with images

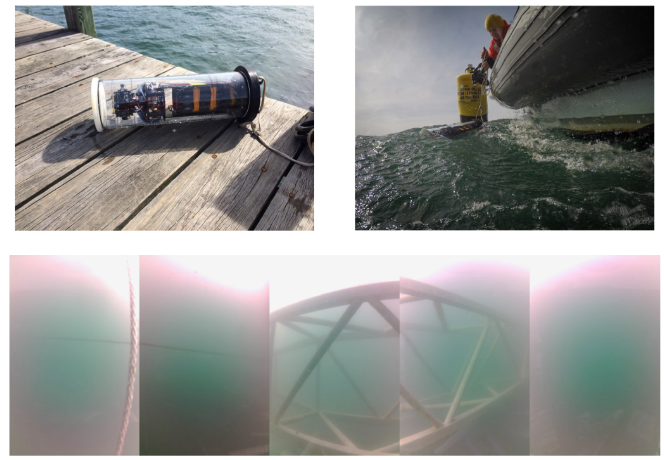

Fig. 9: Kelpcam system prototype testing. Top-left: prototype system on dock. Top-right: deployment of system at Buzzards Bay site. Bottom: stitched image of metal tensioning truss.

containing detections indicated in different colors based on classification, are then plotted on a map layer to support farm monitoring and management.

The prototype Kelpcam system is shown in Figure 9 along with an image captured by the prototype system within the Buzzard's Bay farm site, showing a metal truss which supports kelp long lines. The below processing chains are planned for the eventual system to help manage the quantity of images the system will produce, and provide the vehicle with information on the kelp farm area.

A. *Infrastructure Detector*

Straight lines and edges in underwater camera images of naturally occurring objects are not common, and usually indicate man-made objects such as mooring lines, anchors, floats, trusses and kelp long lines. We plan to detect these features by first finding edge points exceeding a gradient threshold, and then fitting straight lines to these points. Strong edges in an image indicate the presence of man-made structures. An alternative technique would be to apply edge detection and tracking algorithms to sequential images. The locations of detected infrastructure can then be plotted as a map layer.

B. *Kelp Detector*

Kelp, fish and other objects without linear edges may be detected using other methods. Both compressibility and nonuniformity metrics have been shown to mimic human interest ratings in image sequences [23]. A simple method to identify noteworthy images uses JPEG or PNG compression [24]. When empty images of open water are compressed using JPEG compression, the compressor produces small file sizes, such that a simple ranking or thresholding of JPEG file sizes can be used as an object detector. Images exceeding a threshold can be flagged on the map, with detections in an unexpected places or times reviewed by farm operators.

If a textured seafloor or water surface is in view, a nonuniformity score may be more fruitful. Nonuniformity can be quantied by gridding each image into cells and then calculating a histogram or bit-vector descriptor for each cell. Differences between cells indicate nonuniformity in the image, which can then be flagged on the farm map. A sophisticated implementation of this novelty metric was developed and used by Girdhar et al. to develop curiosity algorithms for underwater robots [25][26].

C. Panoramic Images

Vehicle location and pose is recorded with each set of Kelpcam images. After offloading images to the file server, sets of images are stitched together to provide continuous panoramic view from each vehicle location. The locations of captured panoramas are plotted on a map so that individual panoramas can be requested and viewed by a human operator. The map interface allows humans to easily correlate acoustic detections and cross sections with camera images of the same longline location.

VI. Mapping

It is anticipated that longline detections will first be used to produce a simplified 3-D model of the man-made farm infrastructure. Three passes below the farm is anticipated to be enough to produce a reasonable model of each longline as a catenary shape. This model, from Snoopy, will be communicated to Darter. Each vehicle will then use this model to improve sensing quality across the farm: both vehicles to enhance safety and avoid collisions, Darter for getting better images of the kelp, and Snoopy for producing kelp scattering maps.

Data collected from two autonomous vehicles will be offloaded daily and stored in a database, and further post-processed into data products for farmers. The anticipated map-based graphical user interface, also known as geographic information system, will include a map of all longline locations, farm-wide estimates of kelp scattering, Kelpcam detections and locations of available panoramic images. In addition, environmental data may be shown as layers versus depth and x,y across the farm site on the maps. Nautical charts, historical weather and forecasts, aerial and satellite imagery and other data layers may also be imported to complement local surveys. All image locations, with images containing detections indicated in different colors based on classification, are then plotted on a map layer to support farm monitoring and management. This map system is still in development, but is expected to support the management of kelp farms, answering questions such as:

- Are longlines maintaining expected position and depth?
- Is kelp growth uniform over the farm area?
- Does extreme weather event affect kelp growth?
- What is the optimal harvest date and sequence?
- What is the impact of the kelp farm on local nutrients?

VII. Conclusions

Aquaculture monitoring can make use of underwater real-time processing, detection, classification, and ultimately perception tools across acoustic, optic, and environmental sensing domains. For this project, we are looking at autonomously mapping infrastructure, kelp growth, and environmental data for use by kelp farmers in maintenance and decision-making. Initially, we have integrated sensors with two AUVs and deployed those sensors at farm sites in Saco Bay, ME and Buzzards Bay, MA. Initial processing tools were then developed based on the resulting data, and the results show potential for applying underwater perception to real-world sensing and monitoring tasks. The acoustic data in particular was found to provide valuable quantitative information on structural aspects of the farm site, such as longline locations and spatial extent of kelp acoustic scattering. Moving forward, this project will continue to develop the initial techniques demonstrated here at multiple farm sites with real-time processing chains, integrated vehicle adaptive autonomy and inter-vehicle communications. The systems developed here for kelp aquaculture should also be adapted to autonomous monitoring of other species of seaweed and types of aquaculture, such as shellfish and fin fish.

Acknowledgments

First and foremost, the authors would like to thank all of the many engineers, students, administrators and technicians in the Applied Ocean Physics and Engineering Department at WHOI who participated in fieldwork and vehicle preparation, particularly Sean Whelan and Bob Pettit. We would also like to acknowledge Scott Lindell, David Bailiey, and their team at WHOI for supporting our fieldwork at the Buzzard's Bay longline site. Thanks also to the team at University of New England (UNE), including Barry Costa Pierce, Adam St. Gelais, and Kathryn Johndrow, for their assistance and advise in data collection at their Saco Bay kelp site. This work was supported by U.S. Department of Energy Advanced Research Projects Agency-Energy (ARPA-E) under award number DE-AR0000921 and Woods Hole Oceanographic Institution.

References

[1] Utne, Ingrid Schjlberg, Ingrid Holmen, Ingunn. (2015). Reducing risk in aquaculture by implementing autonomous systems and integrated operations. 10.1201/b19094-481.

[2] "Monitoring Macroalgae Using Acoustics and UUV," APRA-E, Release Date: 9/19/2017. [Avail online: https://arpa-e.energy.gov/?q=slick-sheet-project/monitoring-macroalgae-using-acoustics-and-uuv]

[3] Kim J.K., G.P. Kraemer and C. Yarish. 2015. Sugar Kelp Aquaculture in Long Island Sound and the Bronx River Estuary for Nutrient Bioextraction and Ecosystem Services. Marine Ecology Progress Series 531:155-166, DOI: 10.3354/meps11331.

[4] Kim J.K., C. Yarish, E.K. Hwang, M.S. Park and Y.D. Kim. 2017. Seaweed aquaculture: cultivation technologies, challenges and its ecosystem services. Algae 32(1): 1-13 (doi.org/10.4490/algae.2017.32.3.3).

[5] Milledge, John; Smith, Benjamin; Dyer, Philip; Harvey, Patricia (2014). "Macroalgae-Derived Biofuel: A Review of Methods of Energy Extraction from Seaweed Biomass". Energies. 7 (11): 71947222. doi:10.3390/en7117194

[6] Yarish, Charles; Kim, Jang K.; Lindell, Scott; and Kits-Powell, Hauke, "Developing an environmentally and economically sustainablesugar kelp aquaculture industry in southern New England: from seed to market" (2017).Department of Marine Sciences. 4.http://opencommons.uconn.edu/marine_sci/4

[7] "Simrad WBT Mini Miniature wide band transceiver," Kongsberg Maritime AS, 2019. [Avail online: https://www.simrad.com/www/01/nokbg0240.nsf/AllWeb/CC83A234F868D05AC125818C0059CD50?OpenDocument]

[8] "SUNA V2 Nitrate Sensor," Sea-Bird Scientific, 2019. [Avail online: https://www.seabird.com/nutrient-sensors/suna-v2-nitrate-sensor/family?productCategoryId=54627869922gclid=Cj0KCQjwg73kBRDVARIsAF-kEH89zVv2LNf-h85ytfu9qi5oK4-i0RM6fqIMlP8YHWTOmLXjqHmXccAaAo90EALw_wcB]

[9] "Oxygen Optodes," Xylem Inc. Aanderaa Data Instruments AS, 2018. [Avail online: https://www.aanderaa.com/productsdetail.php?Oxygen-Optodes-2]

[10] "ECO Puck," Sea-Bird Scientific, 2019. [Avail online: https://www.seabird.com/auv-rov-sensors/eco-puck/family?productCategoryId=55352274651]

[11] "NBOSI: Cabled CT Sensor," Neil Brown Ocean Sensors, Inc. http://www.neilbrownoceansensors.com/products.html

[12] Minami, Kenji Yasuma, Hiroki Tojo, Naoki Fukui, Shin-ichi Ito, Yusuke Nobetsu, Takahiro Miyashita, Kazushi. (2010). Estimation of kelp forest, Laminaria spp., distributions in coastal waters of the Shiretoko Peninsula, Hokkaido, Japan, using echosounder and geostatistical analysis. Fisheries Science. 76. 10.1007/s12562-010-0270-2.

[13] Blight, A., R. Foster-Smith, I. Sotheran, J. Egerton, R. McAllen and G. Savidge (2011), Development of a Methodology for the Quantitative Assessment of Irelands Inshore Kelp Resource Final summary report, Project Reference: PBA/SW/07/002 (01), Marine Research Sub-Programme, (NDP 2007-13) Series, Marine Institute, Rinville, Oranmore, Co. Galway, Ireland.

[14] Von Borstel, F., de la Rosa Aguilar, E., Suarez Naranjo, J. and J. Gutierrez. (2016). Robotic System for Automation of Water Quality Monitoring and Feeding in Aquaculture Shadehouse. IEEE Transactions on Systems, Man, and Cybernetics: Systems. PP. 1-15. 10.1109/TSMC.2016.2635649.

[15] Fre, M., Alfredsen, J. A. and A. Gronningsater. (2011). Development of two telemetry-based systems for monitoring the feeding behaviour of Atlantic salmon (Salmo salar L.) in aquaculture sea-cages. Computers and Electronics in Agriculture. 76. 240-251. 10.1016/j.compag.2011.02.003.

[16] Zhou, Chao Xu, Daming Lin, Kai Sun, Chuanheng and Yang, Xinting 2018. Intelligent feeding control methods in aquaculture with an emphasis on fish: a review. Reviews in Aquaculture, Vol. 10, Issue. 4, p. 975.

[17] F. D. Von Borstel Luna, E. de la Rosa Aguilar, J. Surez Naranjo and J. Gutirrez Jagey, "Robotic System for Automation of Water Quality Monitoring and Feeding in Aquaculture Shadehouse," in IEEE Transactions on Systems, Man, and Cybernetics: Systems, vol. 47, no. 7, pp. 1575-1589, July 2017. doi: 10.1109/TSMC.2016.2635649

[18] Martinez-de Dios, J., Serna, C., Ollero, A. (2003). Computer vision and robotics techniques in fish farms. Robotica, 21(3), 233-243. doi:10.1017/S0263574702004733

[19] Muoz-Benavent, P. Andreu-Garca, G. Valiente-Gonzlez, Jos M. Atienza-Vanacloig, V. Puig-Pons, V. and Espinosa, V. 2018. Enhanced fish bending model for automatic tuna sizing using computer vision. Computers and Electronics in Agriculture, Vol. 150, Issue. , p. 52.

[20] Muoz-Benavent, Pau Andreu-Garca, Gabriela Valiente-Gonzlez, Jos M Atienza-Vanacloig, Vicente Puig-Pons, Vicente and Espinosa, Vctor 2018. Automatic Bluefin Tuna sizing using a stereoscopic vision system. ICES Journal of Marine Science, Vol. 75, Issue. 1, p. 390.

[21] Al-Jubouri, Qussay, et al. "Towards automated length-estimation of free-swimming fish using machine vision." 2017 14th International Multi-Conference on Systems, Signals Devices (SSD). IEEE, 2017.

[22] Takagi, Motoki Mori, Hayato Yimit, Adiljan Hagihara, Yoshihiro and Miyoshi, Tasuku 2016. Development of a Small Size Underwater Robot for Observing Fisheries Resources Underwater Robot for Assisting Abalone Fishing . Journal of Robotics and Mechatronics, Vol. 28, Issue. 3, p. 397.

[23] Grabner, Helmut, et al. "Visual interestingness in image sequences." Proceedings of the 21st ACM international conference on Multimedia. ACM, 2013.

[24] Schmidhuber, Jrgen. "Driven by compression progress: A simple principle explains essential aspects of subjective beauty, novelty, surprise, interestingness, attention, curiosity, creativity, art, science, music, jokes." Workshop on Anticipatory Behavior in Adaptive Learning Systems. Springer, Berlin, Heidelberg, 2008.

[25] Y. Girdhar, G. Dudek. (2014). Exploring Underwater Environments with Curiosity. Proceedings - Conference on Computer and Robot Vision, CRV 2014. 104-110. 10.1109/CRV.2014.22.

[26] Y. Girdhar, P. Giguere, and G. Dudek, Autonomous adaptive exploration using realtime online spatiotemporal topic modeling, International Journal of Robotics Research, vol.33, no.2, pp.645-657, 2017.