High Frequency Side Scan Sonar Fish Reconnaissance by Autonomous Underwater Vehicles

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Abstract

A dichotomy between depth penetration and resolution as a function of sonar frequency, draw resolution, and beam spread challenges fish target classification from sonar. Moving high frequency sources to depth using autonomous underwater vehicles (AUVs) mitigates this and also co-locates transducers with other AUV-mounted short-range sensors to allow a holistic approach to ecological surveys. This widely available tool with a pedigree for bottom mapping is not commonly applied to fish reconnaissance and requires the development of an interpretation of pelagic reflective features, re-visitation of count methods, image-processing rather than wave-form recognition for automation, and an understanding of bias. In a series of AUV missions test cases, side scan sonar (600 and 900 kHz) returns often resolved individual school members, spacing, size, behavior, and (infrequently) species from anatomical features and could be intuitively classified by ecologists - but also produced artifacts. Fish often followed the AUV and thus were videographed, but in doing so removed themselves from the sonar aperture. AUV-supported high frequency side scan holds particular promise for survey of scarce large species or for synergistic investigation of predators and their prey because the spatial scale of observations may be similar to those of predators.

CJFAS Keywords: Survey, Acoustics Equipment, Sampling, Remote Sensing, Pelagic Fishes

Other Keywords: fish, side scan sonar, autonomous underwater vehicle, imaging

Introduction

Since the discovery of the dynamic deep scattering layer in the 1940s, sonar has developed as the primary tool for remote sensing of marine biomass. Fish reconnaissance has developed since then as both a science and a commercial application to include split beam, spread spectrum (CHIRP), multibeam, imaging, and side scan sonar (SSS) transducers (Hewitt et al. 1976, Farmer et al. 1999, Makris et al. 2006, Boswell et al. 2008, Pena et al. 2014). Continued development is supported by a lexicon for characterizing acoustic backscatter from fishes (Kalikhaman and Yudanov 2006), but classification and enumeration remain a challenge (Demer et al. 2009). Interpretation of reflected low frequency sonar (LFS, here referring to ~40 to 200 kHz) commonly used in fish finder applications is based primarily on quantification of echo strength and resonance relative to the impulse (Nakken and Olsen 1977, Kieser et al. 1993, Bertrand et al. 1999, Sunardi et al. 2008). Low frequency (LF), long wavelength waves echo off proportionately smaller objects as non-intuitive Rayleigh scatter and this is sensitive to the fish's tissue density, the presence or absence of gas bladders and their shape, musculature, recent depth "history", polarity and orientation within a school, gut fullness, orientation to the sonar source, and the number and distribution of individuals within a school (see review by Kalikhaman and Yudanov, 2006, and numerous papers in a special symposium publication, see Demer et al. 2009). The resolution of LF is further constrained to rendering of the reflection on a limited pixel field so that, especially over long ranges, schools rather than individual fish or their features are rendered as an object, especially since scattering organisms include species with solitary, aggregating, or schooling habits, and can range three orders of magnitude in individual body length from cm to m scale (Pena et al. 2014). Over long distances, the beam also spreads, decreasing resolution. The issue of wavelength versus animal size in sonar scatter is well recognized, since lower frequencies have been necessary to penetrate ocean depths below a surface survey vessel. Thus, investigation of scatter from low frequency sonar remains an important topic of research.

Complementary to further development of LFS is the application of high frequency sonar (HFS, 500 - 1000 kHz) by sinking the HF transducers to the depth of interest either on tow cables or mounted on autonomous underwater vehicles (AUVs). HFS, and especially high frequency side scan sonar (HFSSS) produces imagery that is intuitive in the lateral two-dimensional field, and this can include imagery of animals in the water column (O-Driscoll 1997, Grothues et al. 2009, Holliday et al. 2009). (Wavelengths of size similar or smaller than the target fish echo as Geometric scatter to produce an echogram with features of the target's shape and size.) The application and capability of HFSSS has been greatly increased in recent years, but primarily for the use of bottom imaging to detail benthic habitat features rather than fish themselves (e.g. Able et al. 1987, Bell et al. 2006). HFSSS is also frequently mounted on AUVs for military, geological, and anthropological tasks (Hibbert 1997, Hagen et al. 2003, Chapple 2009). While single and multibeam up and down-looking LFS (Fernandes et al. 2000, Trenkel et al. 2009, Scalabrin et al. 2009), and even cameras (e.g. Tolimieri et al. 2008, Smale et al. 2012, Seiler et al. 2012) have been deployed on AUVs specifically for fisheries applications, HFSSS use on AUVs is still largely unexploited for fish reconnaissance, perhaps owing to its pedigree as a tool for imaging bottom bedforms. In fact, water column targets are typically removed when producing side scan "mosaics" that stitch individual image files into bottom feature maps.

The goal of this paper is to describe fish data from pelagic HFSSS on AUVs, accounting for differences from common near-surface vessel-mounted or towed applications. The specific motivation for the use of two (600 and 900 kHz) HFSSS systems discussed in this paper was to employ their imagery for: 1) mapping bathymetry and bedforms in an experimental area to aid in modeling propagation along lower frequency (0.7 to 2 kHz range) acoustic paths (Newhall et al. 2016), and 2) to provide meter-scale information on the distribution of fish and other biota for acoustic scattering experiments. This paper focuses on the second of these motivations, although the AUVs used were built for tasks like the first. Basic HFSSS units are a commercial, off-the-shelf (COTS) technology that many AUV owners have incorporated into their vehicles. They are relatively inexpensive, and simple to use for bottom mapping. It is also well known that such systems see objects in the water column such as fish; since this data is available, even if it is not optimized for fish detection and imaging, it can and should be used to augment other means of examining fish. Currently there is no common practice for deploying, interpreting, and communicating results of HFSSS on AUVs for fish, especially in the deep water column for pelagic species where this presents special opportunities. In particular, we address four broad themes including benefits and constraints. These are:

1) The co-location of sonar with other short-range sensors (hydrographic, photographic) allows holistic ecological surveys.

2) Interpretation of these surveys requires the development of a standard and wider recognition for reflective features and understanding of distortion specific to HFSSS in the water column, especially as this can then be automated through image-processing rather than wave-form processing.

3) The use of transect methods to count fish is appropriate, but requires review of the statistical methods applied to those from other platforms as well as new empirical studies to account for the mechanics and biases of HFSSS on an AUV platform.

4) The relationship between the AUV and fish behavior must be further investigated.

Here, we discuss these issues with data from several AUV missions in coastal and continental slope habitats.

Materials and Methods

Sonar returns discussed here are primarily from six AUV missions, some conducted specifically for sonar fish reconnaissance, but examples of features from other missions are also shown in order to illustrate specific points. All missions utilized REMUS-100 model (Hydroid, Inc. Pocasset, MA) vehicles from Woods Hole Oceanographic Institution or Rutgers University. The base REMUS-100 AUV is a 1.6 m long x 0.8 diameter torpedo-shaped vehicle driven to speeds of up to 5 knots by a single stern propeller. Although specifications differed among these vehicles based on their specialized sensor packages, all supported a two-channel (port and starboard) Marine Sonics Technology (White Marsh, Virginia) side scan sonar system operating at either 600 or 900 kHz, a YSI conductivity-temperature sensor (CT, Yellow Springs Instruments, Ohio) reporting every second, and two (upward and downward looking) Workhorse 1200 kHz acoustic current Doppler profilers (ADCP, Teledyne RD Instruments, Poway, California). The Rutgers AUV also hosted colored dissolved organic matter, chlorophyll-a (both Wet Labs, Inc., Philomath, OR), and dissolved oxygen (Aanderaa Analytic Instruments, Bergen, Norway) optical sensors. During several of the missions discussed, these vehicles also supported GoPro Hero® high definition (HD) video cameras. Missions last up to 10 h.

Reconnaissance missions over the continental shelf of North Carolina were conducted in 2011 and 2012 primarily to locate and identify fish targets to study the scatter and attenuation of low frequency sound (Newhall et al. 2016). In 2011, three consecutive missions across the shelf emulated a single long transect at a depth of 15-20 m, with an additional partial leg beyond the shelf break following the contour to 80 m, but returning at the 20 m level to finish the transect. Only the upper layer of the transect is analyzed here. In 2012, passive hydrophones were moored in vertical stationary arrays, and a moving low frequency source (also AUV-mounted) navigated through the study area. Low frequency (0.7 – 2 kHz) scatter and attenuation was characterized by calculating the difference between the (relatively) un-attenuated signal and that which was recorded by the passive hydrophone array on the other side of or oblique to fish. This required knowledge of the distribution, identification, number, size, and orientation of potential target fish, which was provided by HFSSS from the three AUVs navigating similar paths at different depths, and was complemented by cameras (Newhall et al. 2016). Other missions discussed here were pilots in preparation for that work, or were tasked with tracking fish implanted with acoustic tags for which the LFSSS and other sensors provide complementary data (e.g. Grothues et al. 2009, 2010, Coleman 2015), including unpublished results from missions in the Gulf of Mexico and over the Hudson Canyon off New Jersey.

Sonar imaging

Echoes from the AUV's HFSSS are mapped to a pallet of 512 pixels cross-track (see Table 1 for specifications). Echoes may come from many directions in a disk-like configuration (or at least a lobed approximation of such) normal to the vehicle's path, including from above the vehicle, so that a cylinder (or approximately so) is imaged as the AUV moves forward (Figure 2). However, if the sea bottom intersects this cylinder as a plane because of a low altitude-above-sea-bottom mission, the imaged volume is reduced. Further, objects in the water column may be masked from bottom or surface returns because the image is not vertically explicit as it is for split beam or multibeam sonar (Trevorrow 2001). The downward looking form of a broad or lobed fan beam is approximated only when the source is near the surface so that only the lower half or less of a horizontal cylinder is imaged (Figure 2). Because the pixel number is set, constraining accepted backscatter recording to a shorter delay (and therefore distance) provides higher pixel density for a given area. The re-interpretation of

HFSSS applied from an AUV well below the surface and well above the bottom is an important consideration of this paper and is reviewed in the Results section below.

Data Analysis and Automated Processing

HFSSS returns were reviewed first by eye in the "waterfall" mode of the host software (SS-Review PC, Marine Sonics Inc.), which represents sections of continuous records as "tiles" of two-dimensional images with the x-axis as the cross-field range and the y-axis as elapsed time (60 s) approximating distance (typically 130 m due to the commonly used 1.8 m/s AUV speed) along the mission path (transect). The images were not stitched together into mosaics for review and the water column was not removed. Reviewers marked the location of likely fish targets with a unique identifier and noted their latitude, longitude, and time stamp (to the second). In the case of large fish targets, they also noted the length of the target image, and in the case of fish schools, the area occupied by the visible part of the school. Targets were classified based on characteristics of size, shape, number, spacing, and within-group orientation. Artifacts that could lead to misinterpretation of HFSSS data were also identified.

The time stamps of targets were matched with the time stamped data of the AUV's navigational and sensor data stream so that the target could be not only geo-referenced but resolved into multivariate environmental space of temperature, salinity, and depth (and potentially also dissolved oxygen, chlorophyll-a, and chromatic dissolved organic matter as available from the particular vehicle's sensors). Likewise, video was reviewed and targets identified and their timestamp matched with that of the AUV's navigational and sensor data (including the HFSSS). Video was compared to the image made by the sonar and the lag between likely sonar contacts and video contacts was calculated. The relationship between that lag time and the distance of fish from the AUV during sonar contact was identified and recorded.

As a demonstration of automated processing, a script was developed to find rays (Order Rajiformese) swimming in the water column. Rays are a diverse group of fishes that are distinctive in shape and typically large and sparsely distributed and so are appropriate for a proof of concept for such a technique. The script a) sequentially loaded and read all image files in a directory, each containing a time- and georeferenced section of the data from a mission, b) converted each to a black and white binary image file, c) detected edges (abrupt changes in pixel value in only one of the two dimensions) to segment the image into objects d) measured the potential object shape using an Object Area Distribution and Symmetry Algorithm (OADaSA) Detection and Segmentation process. The scoring of objects based on their symmetry distinguished objects of interest from amorphous segmentation artifacts created during the process of isolating the fish from the background. OADaSA converts an object represented by a set of perimeter points to an object represented by two sets of orthogonal area slices referenced by position along the object's major axis (Figure 3). Area values for each half of the object were then queried for the cumulative distribution/ area balance point, quantitative bilateral symmetry, and percent of total area on each side of the major axis. Identified image objects were scored on the basis of a symmetry rating and grouped into "fish school" and "ray" classes. Fish schools were discriminated from lone fish by using an unsupervised classification algorithm, DBSCAN (Density Based Spatial Clustering of Applications with Noise) which can discover clusters of arbitrary shape (Ester et al. 1996). Image segmentation was accomplished using the basic MATLAB (MathWorks, Inc.) Image Processing Toolbox along with a 2D MATLAB implementation of level set methods (Sumengen 2005; an in-depth treatment can be found in Osher and Fedkiw 2003). These algorithms are treated in the medical imaging (Kockara et al. 2010; Zhang et al. 2008) and machine learning (Chan and Vese 2001) literature, including application HFSSS data (Lianantonakis and Petillot 2005), and are not detailed further here.

Statistical Considerations

Statistical considerations are those that affect the confidence of counting fish and associating them to their environment through an understanding of probability and error sources. These include knowledge of the water volume being effectively sensed, the behavior of fish in response to the AUV that either increases or decreases the probability of their detection (either at all or multiple times including effects of avoidance, attraction, or schooling), classification, and mapping. A body of literature has explored use of different formulae for quantifying organisms in transect sample designs, including algorithms that recognize decreasing probability of detection with distance from the observer, or as a function of angle from the observer, or of the reaction of the observed individuals. As an example for discussion, we use a simple graphical representation of the distribution of different fish classes relative to water characteristics. For common classes of these discrete target objects, we calculated a smoothed estimator of distribution as a probability density function (PDF, kernel method following Worten 1989). Estimates were centered and unit-variance standardized and related to each other through correlation analysis. These were post-hoc and not tested as regression analysis of specific hypotheses, which is beyond the focus of this paper.

Results

A number of image features were intuitively characterized as fish and other animals, including single large but well-defined rays and large and small fish groups. These were resolved into one of six major categories; “rays”, “large singletons”, “loose schools”, “bait balls”, “patrols”, and “followers” (Figure 4). The ray class included members of the whiptail rays (Fam. Dasyatidae, commonly “sting rays”) with thin tails and most of the pelvic fins encompassed by the perimeter of the pectoral fin “disk”, a manta ray (*Manta birostris*, Fam. Mobulidae), with diagnostic cephalic fins well resolved and separated from devil ray (*Mobula hypostoma*), on the basis of size and tail/body ratio) (Figure 4A, top row), and an example of what is likely an Atlantic guitarfish (*Rhinobatos lentiginosus,* the only local member of Fam. Rhinobatidae) but possibly an Atlantic angel shark (*Squatina dumeril*), both of which have similar elongate outlines with separated pectoral and pelvic fins and a fleshy caudal peduncle. "Patrol" referred to highly organized structures, either single or double lines of similar-sized members with even spacing, or sometimes in a "v" shape (reminiscent of flying geese flocks) (Figure 4 A, middle rows). This organization is frequently seen in areal imagery in socially foraging predatory fish such as tuna. These were sometimes imaged in proximity to bait balls. "Followers" referred to fish that paced the AUV abeam so that they stayed within HFSSS aperture to return long sinuous object features from many meters to as much as a km in length (Figure 4A, middle and bottom rows). This behavior is described further below. "Bait ball" designated a tightly packed school of fish, with members spaced equal to or less than a body length from each other, and frequently so tight as to overlap and form a single large image object without texture except at the edges (Figure 4B). These did not show a common axis of travel when members were distinguishable, and numbered typically on the order of hundreds when individuals were distinguishable. In the Gulf of Mexico missions in particular, these tightly packed schools formed lacy structures (Figure 4B bottom right). In some cases, they were apparently under attack by larger predators also visible in the sonar image. The "loose schools" class designated a group of fishes that were clearly oriented to each other, with a common long axis direction and often a well-defined leading but not trailing edge, and members spaced much greater than individual body lengths from each other (Figure 4C top row). These typically contained on the order of tens of members. "Large singletons" referred to large, strongly reflective targets in the water column, either globose or elongate, that were not oriented to other targets or the AUV. They may have included turtles, which were regularly seen on the surface and while diving in the area or potentially large jellies, or any single members of those fish that formed patrols. The "few scattered fish" or "numerous scattered fish" classes reflected the fact that "singletons" were often too common in a single image frame to be counted individually, but while not organized relative to each other were very characteristic of a particular tile. Separation of these classes was subjective. Moreover, these two classes represent an area more than an individual point count, with important consideration to how they should be handled statistically.

Several artifacts were also identified that could have been confused with biota and many of these were clearly above the AUV or even on the water surface, including the underside of the skiff and outboard motor used to launch the AUVs (Figure 4C middle left), vessel wakes, and the undersides of breaking waves. Vertical instrument mooring lines returned crescent-shaped image objects because the radius of the signal/echo path is longer both above and below the depth of the AUV and intercepts only part of the line as a chord through the ensonified cylinder; these could appear similar to "followers" (Figure 4C middle right). On several missions closer to the seabed, returns from the seabed masked portions of schools which were otherwise clearly visible in the water column (Figure 4B middle). When returns were strong, such as of dense aggregations or large fish, these could still be distinguished; further, their acoustic shadows on the seabed could assist in their detection and calculation of their depth (Figure 4A third row left, Figure 4B, bottom row). One type of artifact that could confound both human and simple automated counts is the doubling of images from very strong echo returns (Figure 4C bottom left). This happened particularly from large fish such as amberjack (*Seriola dumereli*) that so closely paced the vehicle that the echo from the back lobe of the transducer on the opposite side of the vehicle registered on the transducer on the same side of the fish with a delay that is characteristically one and a half times the distance between the transducers. Near the bottom, a similar effect results from multipath. Finally, artifacts from acoustic modem calls between the support vessel and the AUV or cross talk from other AUVs in the vicinity could potentially be counted as patrols by novice reviewers or algorithms because of regular spacing and staggering, but these are extremely linear and regimented and typically weaker than fish (e.g. Figure 4C middle right, consequent with mooring line).

Of the 202 total targets in three cross-shelf missions from September 2011 for which they were quantified, the most common type encountered was few scattered fish (64 incidents), followed by bait balls (36 incidents), large singletons (26), patrols (25), loose schools of large individuals (16), followers (11), and rays (3). These were distributed unevenly relative to depth, hydrography, and distance across the shelf in the September survey off Cape Hatteras, NC (Figure 5). Three nominal classes (patrol, bait ball, loose school), were further examined because they were common. The distributions of all three (represented by kernel smoothing) peaked with varying degree of association to the shelf break and the shelfbreak front (Figure 5). Loose schools were most closely associated with the front and rarely were imaged far from it. The distributions of presumed predatory patrols and bait balls were much broader across the shelf and were highly and significantly correlated to each other, with patrols slightly favoring the offshore side of the front. Patrols were also significantly but less strongly correlated with loose schools, but loose schools were not correlated with bait balls at least on the cross-shelf scale (Table 2). During a similar mission over the Hudson River Canyon, NJ, a strong vertical front was not encountered. Salinity was low and generally restricted to a narrow band between 32.2 and 32.7 (except for a very thin surface lens with salinity as low as 30) but temperature difference in 3 strata exceeded 12 ^{o}C. Bluefish (*Pomatomus saltatrix*) were encountered in all of these and in the thermoclines between them (Figure 6).

A review of transect sampling methods and count treatments shows that most are for planar application, such as terrestrial survey or aerial survey of thin ocean surface layer for mammals, tunas, or elasmobranchs (e.g. Leatherwood 1979, Blaylock 1988, Bonhommeau et al. 2010) (Table 3). A potential exception is for diver and submersible transects, but these are generally for reef fish with benthic or structural orientation, rather than for pelagic fishes. In general among the statistical formulae for the estimation of density (D) from animal counts (*n*) is the measure of sighting distance (r), sighting angle (θ), and perpendicular distance (x), for use in an estimator function *a* such that in a transect of length L

$D = n/(2La)$,

to take into account the probability of detecting fauna at different distances or angles. Such functions rest on four assumptions (detection is certain, animals don't move for subsequent detection, sightings are independent, and there is no measurement error) which are rarely met. For example, ground birds are cryptic and counted when flushed, but less so when the counter is distant (Gates et al. 1968). Cetaceans have species-specific avoidance or attraction responses starting many km distant from survey vessels (Palka and Hammond 2001). Therefore, a fixed-width strip estimate creates a bias. In another example, for areal counts of marine animals, the aircraft that hosts an observer itself blocks some angles of vision and is corrected in formula (Leatherwood et al. 1982). For an AUV using side scan sonar, θ is always 90^o and so r and x are the same and are fixed to the accepted echo return delay (here to a distance of 30 m) in the sonar's initialization file. However, the transect cylinder is not perfectly cylindrical, or is potentially weak or distorted outside of stronger lobes, and moreover masking by the bottom returns can cut the effective strip width substantially for some fish like "loose school" but not for others (see examples in Figure 4, also Misund et al. 1995, Trevorrow 2001). Various formulas address such biases as effective strip width and flushing (Table 3). A two-observer system (Turnock and Quin 1991, Buckland and Turnock 1992) is useful in calculating a response bias (attraction or avoidance) by using a second (typically independent) observer team. This is improved by Palka and Hammond (2001) for two teams on a single platform, by looking at orientation of the organisms (in their case cetaceans) to the platform in different quadrats representing independent observations of what cetaceans did as the vessel approached them or left them behind and corrected for potential pre-encounter orientation. In some ways, the two (left and right) sonar channels of the AUV's side scan could emulate the two observer team, although the imaged distance may be much less than the response distance. Coefficients thus need to be developed explicitly for AUVs and the side scan sonars they mount.

Video imagery, as a "second" observer was able to identify a number of the species and also their response bias because the AUV attracted them and because the camera was mounted to face aft (Figure 7). Earlier attempts with forward facing cameras imaged no fish, although followers were apparent in the sonar record. Of 10 imaged species (Table 4), 7 were predatory and these species were also imaged more frequently. These could be seen approaching the AUV from the sides both above (Supplementary Material Video 1, bluefish_clip, Supplementary Material Video 2, tiger_shark_follow) and below (Supplementary Material Video 3, blue_runners_clip, Supplementary Material Video 4, little_tunny), but also from far behind, possibly without having entered the HFSSS aperture (Supplementary Material Video 5, amberjack). Only one sequence showed a bluefish (*Pomatomus saltatrix*) approaching the vehicle from in front and above and then turning sharply to fall in line behind and alongside it with other individuals. However, blue runner (*Caranx crysos*) also followed the AUV after converging on it from all directions in numbers approaching a hundred individuals (see also Newhall et al. 2016) (Supplementary Material Video 3, blue_runners_clip); these are generally zooplanktivores that may take small bait fishes (Carpenter 2002). In one instance, the AUV passed through a school of bait fish < 10 cm length and most likely round scad (*Decapturus punctatus*) which appeared to scatter rather than follow the AUV. Scattering is also visible in HFSSS from another mission (in turbid water that carried no camera) where the AUV passed directly through a bait ball (Figure 4B, bottom left).

Fish that were imaged by camera following the AUV stayed behind it for durations of seconds to several minutes and there was a tendency for larger schools to remain for longer periods (Table 4) (Supplementary Material Video 3, blue_runners_clip). However, calculation of a very long “follower” feature in a mission without a camera shows that at least one individual paced the vehicle alongside for a duration of 3 minutes (320 m). Fish often followed so closely that images were compromised by the AUV’s propeller and control fins given the narrow “head on” view (Supplementary Material Video 1, bluefish_clip, Supplementary Material Video 2, tiger_shark_follow); however, fish broke contact by “peeling” away rather than falling behind or passing the AUV forwards (Supplementary Material Video 6, barracuda) . The peeling away behavior afforded an opportunity for the camera to image the fish in broadside, which aided in identification (Figure 7).

During the time that fish were lined up behind and following the AUV they were not in the HFSSS aperture. Of 46 image contacts with bluefish, only 22 could be associated with corresponding marks in the side scan sonar records, indicating that a number of these individuals were not imaged on sonar around the time that they were detected by the camera. Right-size sonar targets were found between -64.0 to 95.9 s of corresponding video imagery and generally preceded the photo imaged target with a skewed distribution of median -17.5 s and mean -7.7 s, (S.D. = 38.04 s). The distance of contacts corresponding to the video imaged targets range between 20.9 m and 0.5 m, but was uncorrelated with lag time to imagery (rho = 0.18, p = 0.48). Inspection of the residuals showed that most of the variance was accounted for in the near field while distant targets all had longer lag. This is indicative of fish approaching the vehicle from the side and then pacing or falling in behind it, much like a dog attacking a bicyclist. This pattern is readily apparent in supplementary material posted as video imagery (see Figure 7 caption).

Automated detection of objects in 1536 trial HFSSS files from May 2012 cruise off Cape Hatteras, NC, resulted in 324 (21%) sonar image tiles being flagged for further review. Of those, 88 (27.2%) proved to be artifacts of pitch angle created when the AUV ascended or descended (the change in distance to the surface reflection creates a symmetrical "v" with a continuous edge) and were easily identified and eliminated from the list of images of interest. Another 49 (15%) of the 324 sonar image tiles contained fish schools, large fish-like objects, or rays. Of those image objects (n=16) that were first scored by independent human review as rays, 87.5% were also classified as such by the algorithm. "Missed" (relative to human review) detections owed primarily to failure of the segmentation algorithm in separating the ray outline from bottom reflection.

Discussion

AUVs have previously mounted sonar for the purpose of fish reconnaissance, although low frequency (38-200 kHz, see review by Trenkel et al. 2009). Most have been on deep-diving vehicles targeting benthic or suprabenthic fish with down-looking beams where the AUV's proximity allowed differentiation between the bottom and target by increasing local resolution (Fernandes et al. 2003), or targeting anchovy, herring, or krill biomass measures in the "acoustic dead zone" near the surface that would otherwise be directly underneath a surface survey vessel (Scalabrin et al. 2009) using up-looking beams (Breirley et al. 2012). High frequency (700 – 1850 kHz) side and up looking sonar in Tracor Acoustic Profiling Systems have been deployed in somewhat analogous sampling models as presented here to achieve holistic ecosystem measurement at small (zooplankton) scales. In these cases, high frequency sonar was incorporated with low frequency bands and deployed simultaneously with oceanographic sensors and optical instruments to understand trophodynamics as either moored (Holliday et al. 2009) or towed packages (Lbourges-Dhaussy et al. 2009). Both used acoustic returns to create volumetric estimates by size class, with photo imaging or net samples to supervise classifications. The latter coupled this further with traditional low frequency (38 kHz) volumetric assessment of sardine and anchovy distribution. The disparity in scaling of these instruments meant that coupling models relied on kriging between stations separated on the order of 18 km (Lbourges-Dhaussy et al. 2009). There are relatively few published attempts to use HFSSS, in the band spectrum defined here, for fish study on any platform. Of these, most are for sturgeon in riverine or estuarine habitats where the river bed is also imaged and of interest, and where the shadows are also diagnostic (Thomas and Hass 2004, Grothues et al. 2009, Flowers and Hightower 2013). One (Grothues et al. 2009) utilized an AUV, and this also imaged the bottom for understanding this benthic specie's relation with habitat. The combination has not been previously used in pelagic applications. This technology is commonly available but underutilized, perhaps owing to a misunderstanding of its function and interpretation among biologists and the common practice of presenting it in the mosaicked form that eliminates the water column.

Inexpensive HFSSS imaging is not designed to, and will not compete with multi-frequency and broadband backscatter sonars, multi-beam sonars, acoustic cameras, and variants thereof, which also can be incorporated into an AUV payload, for acoustically imaging fish. Instead, it stands to fill an important niche in research on a spatial scale fitting between camera imagery and LF sonar, and differs substantially in applicability and analytical approach. On the fine end of the resolution and range scale, cameras have also been mounted as a primary fish sensing tool on AUVs mostly for benthic fish because the distance to the subject is easily constrained to be in the focal and visibility range by the altitude-over-bottom (Tolimieri et al. 2008, Seiler et al. 2012, Smale et al. 2012). These applications utilize static frames and machine learning for image recognition similar to that described for HFSSS here. The AUVs used (e.g. SeaBED) have accordingly been slow-moving, purpose built machines (Hsing et al. 2003). On a slightly longer range scale, multibeam imaging sonar extends vision to approximately 20 m, but also differs from single beam HFSSS in that it produces moving (video-like) images (see review by Martignac et al. 2012). Imaging sonar in fisheries applications is usually statically mounted in constrained areas such as rivers or fish ladders (but see Able et al. [2013, 2014] for examples of mobile deployments) and moving fish are thus differentiated from a static background (Boswell et all 2008); but it is side-looking and HF (typically above 900 kHz) (Martignac et al. 2012). Imaging sonar has been mounted forward-looking on a REMUS AUV but for obstacle avoidance (Hsieh et al. 2005), not for fish surveys. Between these and LFS, AUV- mounted HFSSS is demonstrated here to be useful to examine especially the distribution and association of infrequently occurring pelagic meso-level consumers (e.g. scombrids, carangids, and rays) as individuals or small (10s of individuals) schools. It is well placed, for example, to supplement fishery-dependent long-line by-catch data for mobulid ray stock-assessment (e.g. Mas et al. 2014). It is a fishery-independent method that also complements satellite telemetry of the same (Jaine et al. 2014), which is reliant on ray catches and very few individuals. However, this needs to be further developed in application. On the previous AUV/HFSSS riverine application, the size of adult sturgeon at 1 - 3 m long is diagnostic of identity and shadows on the bottom also helped reveal features such as the heterocercal caudal fin and posterior dorsal fin placement. This will not always be the case in pelagic applications, but the images of rays shown here demonstrate the potential.

While there is little diversity in the structuring seen in HFSSS images of sturgeon (they are all single fish or milling aggregations), these studies are noteworthy because they demonstrate the applicability of HFSSS to the survey of fish that should not or cannot be easily captured for survey, or where density or abundance estimates from capture methods are seriously biased by the behaviors of the fish or by the differences in the environment over which they are distributed. The use of an AUV by Grothues et al. (2009) was helpful but not critical to accomplishing the survey task (it was incidental to an AUV-supported telemetry project tracking sturgeon). The AUV’s role in coupled fish/hydrographic survey becomes important in pelagic systems where search areas are wide and habitat is defined by fronts and fluid structures that may be just meters in thickness but occur well below the surface. In this, the few non-sturgeon studies of HFSSS use, even without AUVs, are also noteworthy. In general, the impetus for side scan use has been to survey fishes in shallow water or at least shallow depth strata, either in rivers (Burwen and Fleischman 1998) where down looking sonar is ineffectual at finding near-surface fish because only a very small volume right under the ship can be ensonified, which is also typically avoided by the fish (Ona and Torreson 1988, Gerlotto and Freon1992, Soria et al. 1996, Trevorrow and Claytor 1998). Trevorrow (2001) used 300 kHz, mid-frequency by our definition here, to observe fish in near-surface water when resolving depth at high precision was specifically the issue. In that case, the issue of low depth precision noted by us was resolved with a narrow beam sector scanning instrument (Trevorrow 2001). Side scan is also applied at low frequency for this reason; LFSSS at 12 kHz (Farmer et al. 1999), and 100 kHz (Trevorrow 1997) was used to study salmon (*Oncorhynchus spp*) and herring (*Clupea* or *Alosa*) in broad shallow water bodies. The side-looking sonar arrays were able to image a much greater volume of water, with the long-distance penetration advantage of low frequency sonar being otherwise wasted in shallow water. These arrays were also towed below the surface (at 35 m in 60 to 220 m total water depth, Farmer et al. 1999) similar to the way our AUVs were deployed. However, as appropriate to the applied frequency, fish were still classified and quantified based on reverberation ratios. Discrete salmon targets (~ 1 m) and schools (but not individuals) of the smaller (<0.4 m each) herring were identified. A study in Tasmania utilized side scan sonar in order to survey the patchiness of forage fish schools that form near the water surface, which is difficult to do from a surface vessel with downward looking sonar (O'Driscoll 1997). That study applied sonar at 130 kHz, which, although intermediate in frequency relative to the individual size of fishes studied (barracouta, *Thyrsites atun*; jack mackerel, *Trachurus murphyi;* slender tuna, *Allothunnus fallai*) and probably sprat (*Sprattus antipodum* or *S. muelleri*), produced intuitive imagery of the schools that they form and were useful in relating them to the presence of marine birds and hydrography.

The tasking of AUVs to find and identify aggregations or schools of medium-sized fish in open water in our study was stimulated by the synergistic use of AUVs for a different purpose. One AUV was tasked with rapid mobility of an omnidirectional LF sonar source to study scattering and attenuation (Newhall et al. 2016). Two additional AUVs roved over the same area to identify the presence, size and location of fish schools that could be targets of the LF scattering experiment. The experiment highlighted strengths and constraints in applying this technology in a primary, rather than support role. These include capability, bias, classification, and automation, as treated below.

Capability

The use of an AUV to support deep HFSSS emulates the use of aerial photography to document the presence of fish and mammals that are not amenable to trawl, net, or capture using other fishery-dependent methods, but without the bias of being limited to animals using the very uppermost (1-4 m) of the water column (Bonhommeau et al. 2010). It also emulates the use of drop cameras which are often used to ground truth LFS, but at an intermediate scale between LFS and cameras in both resolution and range. Further, it offers methods for ground truthing that are not available to aerial survey, such as close-up photography and acoustic tag detection of sentinel individuals from the same AUV platform and importantly, for statistical association with their environment. Acoustic telemetry of tagged individuals from an AUV has been demonstrated in two very different applications: the continuous following of a given targeted individual shark (Manii 2012) and the mapping of a number of different individuals to describe movement and relationship to hydrography (Eiler et al. 2014, Coleman 2015), including together with verifying the identity of sonar contacts (Grothues et al. 2009, Grothues et al. 2010). Payload control, the ability to autonomously reroute an AUV in mission in response to incoming data such as telemetry (Grothues et al. 2010, Manii 2012) in order to acquire better or more data in patchy systems, is rapidly developing and will also complement the development of adaptive acoustic sampling designs practiced by piloted vessels (e.g. Harbitz et al 2009).

An important aspect of the use of AUVs for fish reconnaissance is the concurrent oceanographic data which is collected (sensu Lebourges-Dhuassy et al. 2009 using towed equipment). During the pilot study in September, 2011, the hydrographic conditions included a near surface buoyant, low salinity plume which was likely associated with the Chesapeake Bay outflow plume. This plume had a cross-shelf extent of at least 35 km and was much larger in spatial extent than the normal 5-7 km cross-shelf scale. The observations in September, 2011 were shortly after the passage of Hurricane Irene, which caused extensive rainfall and subsequent flooding on the eastern seaboard. Similarly, the observations in May, 2012 occurred during anomalous warming conditions (Chen et al. 2014) over the Middle Atlantic Bight and Gulf of Maine. Thus, the use of the AUV platforms also provide a detailed high-resolution hydrographic context for the interpretation of the spatial and temporal variability of the fish distributions.

Bias

Bias is a problem with all fisheries and scientific survey techniques and perhaps especially so in the case of pelagic environments, where different species are sparsely and patchily distributed over wide potential areas not associated with static structures (such as benthic forms), or are associated with dynamic hydrographic or biological structures that are not always apparent until after surveying (Pennington 1983, Boulinier et al. 1998, Kimura and Somerton 2006, Davoren 2013) or range widely in size. Non-extractive surveys are less biased to inter-species relative abundance and size than capture sampling (Silveira et al. 2002) because different capture techniques invariably target aspects of habit or morphology (e.g. bait attraction, thigmotaxis or phototaxis, trawl or gill nets, etc.) that differ among species. Acoustic surveys are non-extractive, and low frequencies can sample wide areas quasi-synoptically to resolve patchiness so that it can be treated statistically (Kimura and Somerton 2006). While the AUV potentially mitigates some bias in the acoustic approach, it differs from that of vessel mounted and perhaps towed sonar in a number of respects.

Bias associated with use of an AUV to mount HFSSS includes the fact that the two dimensional imagery flattens a three dimensional distribution, especially in the absence of ocean floor returns upon which shadows can be seen and used to calculate altitude over bottom. This has been addressed technically by multibeam sonar that divides the ensonified area among many thin, spatially explicit beams (e.g. Gerlotto et al. 1999) and which is becoming available on AUVs, but is still uncommon and expensive. However, the depth uncertainty of single beam HFSSS is limited to the sonar's small range. In understanding these limits, a mission is seen to approximate a distorted tubular transect, and the limitation can be used to define depth sample strata. Another bias is the selective removal from sonar "vision" by following behavior, and the lengthening of acoustic images by along-side pacing behavior, and conversely it's shortening when the target moves in retrograde. A better understanding of this bias could be achieved through studies in instrumented observatories that can follow numerous fishes in fine scale, such as by Time Difference of Arrival (trilateration) of high signal rate acoustic telemetry (Cooke et al. 2005, Brown et al. 2010) while AUVs are run through the observatory. The use of acoustically tagged sentinel animals can also be used to measure the likelihood that individuals or even schools are acquired multiple times as a function of search path geometry following a mark-recapture model. In practice, this can be mitigated by the use of cameras to document following and calculate an error rate as we did here. The attraction that causes bias is also a benefit to recognizance because it provides some level of ground truthing by attracting fish that are in the search area but potentially beyond the HFSSS range into both the sonar and camera aperture. These same issues appear as the debate over the use of baited versus un-baited static camera traps (Harvey et al 2007, Schobernd et al. 2014). The developing conclusion in those studies is that baited camera traps tend to document higher and more correct species diversity values while possibly overestimating abundance (or density) of scavenger of predatory species at least on reefs because these species might not otherwise be seen at all. Assemblages resolved from baited camera samples were more discriminant with respect to habitat, and replicate samples from baited cameras had less variance than unbaited cameras (Harvey et al. 2007). The greater statistical confidence results primarily from the assurance that hard-to detect species show themselves (Harvey et al. 2007). These findings are favorable to the use of AUVs, which may in essence bait themselves for the scarcer fast moving predatory species such as sharks and tunas. However, continued study of the extent and mechanism of the bias is necessary. In the baited camera trap analogy, the type of bait and direction and extent of the scent plume may impact the results (Harvey et al. 2007). Likewise, and also similar to divers (Watson and Harvey 2007) the AUV has a number of features which may be species-specific attractants and may work over different ranges and directions, including sound in a wide frequency band ranging from the acoustic instruments themselves to the mechanical (motor, bearings, and servos) and hydrological noise of propulsion, and also lights (blue, yellow, green, and red) from the dissolved oxygen, CDOM, and chlorophyll *a* sensors, painted hull color, and electrical and magnetic noise from the processors and navigation instruments. The contribution of these factors to attraction is testable by masking, muting, or changing the colors or sources in replicate missions as has been done on a limited basis for fisheries survey ship sounds (Handegard et al. 2015) especially if done in an observatory such as mentioned above.

Pelagic fish are typically remote and thus unobservable other than by sonar, are often randomly and sparsely or patchily distributed, do not cooperate with acousticians to present a good aperture, and if held in tanks are no longer representative of their natural state. Even tethering active fishes changes sonar returns although it can provide important baseline information (Nakken and Olsen 1977).

Identifying individuals in order to build supervised classification schemes is typically done through parallel sampling programs that seek probabilistic determination (ground truthing) or actual target identity (verification) (e.g. Bertrand et al. 1999, Doray et al. 2007). The best resolution to uncertainty in the classification application comes from a combination of both. The current project relied on verification by video imaging and also ground truthing by fishing, which confirmed the suspected identity and size of little tunny (*Euthynnus alletteratus*), dolphinfish (*Coryphaena hippurus*), amberjack (*Seriola dumereli*), blue runner, and posited the identity of bait balls as round herring (*Etremeus teres*) and Spanish sardine (*Sardinella aurita*) in September 2011 and May 2012, respectively, as the exclusive fish gut contents of tuna caught in the study area. This is because an echogram contains information not just about individual targets but about the dynamics of targets with each other; in essence there is ecological information that can help inform sonar interpretation and ecological knowledge that could be gained from sonar if the approach allowed synergistic sampling of other variables (Shen et al. 2009). The class names we chose are expressive of commonly occurring intuitive forms and carry some ecological interpretation. We accept that they are not exhaustive; rather a systematic refinement of classification is introduced here as a challenge for further work.

Automation

There are a number of Machine Learning (ML) algorithms for multi-labeling (Bishop 2006). These find features of an image including, for example, gradients in pixel value and relate the shape and distribution of these to training sets identified by the researcher. Shapes or other underlying features will then be used to classify similarities and differences using such tools as principle components analysis, cluster, or similar ordination analysis, and will also produce hydrographic association statistics (e.g. with principal or canonical correspondence analysis, Lebourges-Dhuassy et al. 2009 Shen et al. 2009). Classification from acoustical backscatter properties through such algorithms is not new to fish reconnaissance in low frequency down-view sonar (e.g. Cabriera et al. 2009 and Charef et al. 2010, both using neural net and discriminant function algorithms for sonograms made at 38 kHz), but the algorithms of choice will likely differ because of the plan view and resolution of individual fish in the school. The use of fast Fourier transform (FFT) algorithms, which parse the grey-scale value of pixels of an image space into vectors of different frequencies, are particularly interesting for discriminating among types of schooling fishes because of the repetitive and even nature of the high reflectance (fish) and low reflection (school interstitial space) of the image. This method is useful in classifying ocean bedforms (Fakiris and Papatheodorou 2009), of which some, such as sand ripple fields, are similar to fish schools in appearance.

Robots, and AUVs in particular, have demonstrated a niche for themselves in performing many other mundane and deep tasks and especially benthic side scan survey (Hibbert 1997, Moline et al. 2005, Clarke et al. 2010), including side scan surveys of fish (Grothues et al. 2009). They can work under ice with far less disturbance than for a towed system below an icebreaker (Fernandes et al. 2003). Further, they can work from and alongside vessels already engaged in other sensor deployment tasks to greatly increase the survey footprint with little or no additional crew. Thus, they can complement other survey methods. Ongoing work promises cooperative-adaptive swarming behaviors (Belbechir et al. 2010). Many engineering challenges have been met to bring AUVs from experimental vehicles to applications, but further challenges must be met in this new task. In regards to the search for sparse large fish, OADaSA allowed high performance in images with poor segmentation properties. The large cut in human processing time and high fidelity detection rate could make AUV-supported side scan sonar a viable tool for surveying rays and other pelagic fish research. It is relatively immune in this application to problems that arise for automated side scan sonar detection by AUV of objects on the seabed, such as anti-shipping mines (Chapple 2009). The algorithm accuracy can be improved by implementing different segmentation techniques. The most exciting implication of this is the formation of a basis for in-situ classification to drive AUV responsive navigation (payload control), including for other fishes.

Further study promises to let AUVs search pelagic environments with patchy fish distribution in the same way that the predators do, such as the application of Levy-flight or run-and-tumble search path models (Humphries et al. 2010, Saldivar 2012, Watkins and Rose 2013) that use locally-sensed environmental cues to modify the AUVs' navigation.

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Table 1. Side scan sonar specifications

	Rutgers AUV	WHOI AUVs (2)
Frequency	600kHz	900 kHz
Operating Range	75 m	40 m
Horizontal beam width	0.4^{o}	0.4^{o}
Vertical beam width	40^{o}	40^{o}
Transducer depression angle from horizontal	10^{o}	10^{o}
Transmission pulse (Tone burst)	10 us	6.7 us
Digital across-track resolution	~ 1 cm, range dependent	~ 1 cm, range dependent
Digital along-track resolution	~ 2 cm, SOG dependent	~ 2 cm, SOG dependent
Acoustic across-track resolution	1.5 cm	1.0 cm
Acoustic along-track resolution	15.24 cm	10.16 cm
End of near -field	9.3 m	6.2 m

Table 2. Correlation between standardized particle density function estimates of distribution of 3 nominal fish classes (patrol, bait ball, and loose school) with distance across the continental shelf of Cape Hatteras, North Carolina, USA based on side scan sonar survey by an AUV (See Figure 5).

	$F_{\text{bait ball}}$	$F_{\text{loose school}}$
F_{patrol}	**rho = 0.8988** **p < 0.0001**	**rho = 0.3549** **p = 0.0003**
$F_{\text{bait ball}}$		rho = 0.0978 p = 0.3329

Table 3. Some modifications of line transect estimators and their application to AUV supported fish recognizance.

Estimator	Modification	Relation to AUV	Citations
Hayne and Modified Hayne	Addresses bird flushing response to investigator	Fish react to AUV, but response distance is unknown	Gates et al. 1968 Burnham and Anderson 1976 Gates 1979
Fourier Series Estimator	Modifies transect width based on observed distribution of x	Recognizes the potential for echo weakening with distance from AUV	Burnham et al. 1980
Shape restricted estimator	Concave curvilinear decrease in detection probability relative to x	May be useful for transect width shoulder created by bottom reflection masking of fish	Johnson and Routledge 1985
View hindrance correction	x ~ x/2	Moves transect centerline outboard to assume blind spot near for aircraft, maybe similar to reduction under nadir	Leatherwood et al. 1982.
Distance methods	Clumped and fixed distributions	May be useful for schooling fish	Buckland 1985

Quadrat and point count Methods	Generally for dense non-motile organisms/plants	May be useful for classification of regions based on tiles, such as FSM/MSF	Schweder 1977
Responsive Movement	Modification of distance methods using two observers for 4 sectors, takes animal orientation relative to platform into account as bias estimates	Left and right sonar channels can act as two observers, but describing orientation is from sonar is difficult, AUV has only 2 sectors	Turnock and Quinn 1991. Buckland and Turnock 1992. Palka and Hammond, 2001.

Table 4. Incidents of fish imaged in the aft-facing video camera and the mean duration of following behavior. No following behavior is indicated by “0”.

Species	Timed incidents	Mean Duration (s)
Blue Runner (*Caranx crysos*)	7	65
Amberjack (*Seriola dumereli*)	10	138
Tiger shark (*Galeocerdo cuvier*)	2	67
Other shark	2	25
Barracuda (*Sphyraena barracuda*)	1	26
Little Tunny (*Euthynnus alletteratus*)	2	30
Dolphin fish (*Coryphaena spp.*)	1	3
Bluefish (*Pomatomus saltatrix*)	43	11
Round Scad (*Decapturus punctatus*)	1	0
Stingray (*Dasyatis spp.*)	1	0

FIGURE CAPTIONS

Figure 1. Schematic showing flattening and then removal of water column echo returns for georectification and preparation of alignment into mosaics of multiple "tiles". Mosaic not shown.

Figure 2. Above) Schematic of the approximate split disk ensonified area around a submerged AUV or tow body. Below) Translation of the features normally seen in an un-georectified image tile where the sss intersects both the bottom and the surface. No fish are shown in this image.

Figure 3. Automated processing of side scan images for rays as a model for algorithm development to extend to fish school classification. A) The image is converted to black and white format, objects are delineated by edge-detection and segmentation, and are filtered by size. A guitarfish, recognized on the basis of separated pectoral and pelvic fins and thick tapering tail appears in the image tile at lower left. B) Targets are measured along longest and orthogonal axis. C) The distribution of width (y) along various distances of length (x) is calculated to define shape, by an Object Area Distribution and Symmetry Algorithm (OADaSA) for one parameter of classification.

Figure 4. Diversity of fish classes imaged by HFSSS. A. First row, "rays" including manta and sting rays. Second and third row left, "patrols". Third row right and fourth row, "Followers". B. "Bait balls" C. First row, "Loose schools" . Second and third rows, artifacts including underside of semi-rigid skiff, mooring line, and doubling of fish reflectors pacing the AUV.

Figure 5. Cross-shelf distribution of incidents of "bait ball" and "patrol" classes off Cape Hatteras, NC in the shallow transect. Relative to temperature and salinity as measured by the AUV. Ascending spikes in the temperature record and descending spikes in the salinity record occur when the AUV

periodically ascends through warmer fresher layers to the surface to check it's estimated position using GPS and thus profiles the water column.

Figure 6. The temperature and salinity (TS) experienced by bluefish (open blue circles) during their approach and photo imaging of the AUV superimposed over the total TS field encountered by the vehicle during a mission over the north western Hudson River Canyon off New Jersey. Temperature and salinity of bluefish occurrence are linearly interpolated from the first sighting of the fish in the camera using the nearest (every 1 s) temperature and salinity logged by the AUV.

Figure 7. Screen grabs of fish peeling away from or approaching (shark) the AUV after or prior to following. Top left, bluefish, top right, tiger shark, bottom left, blue runner, bottom right, little tunny. Video of these and additional interactions are available as Supplementary Material.

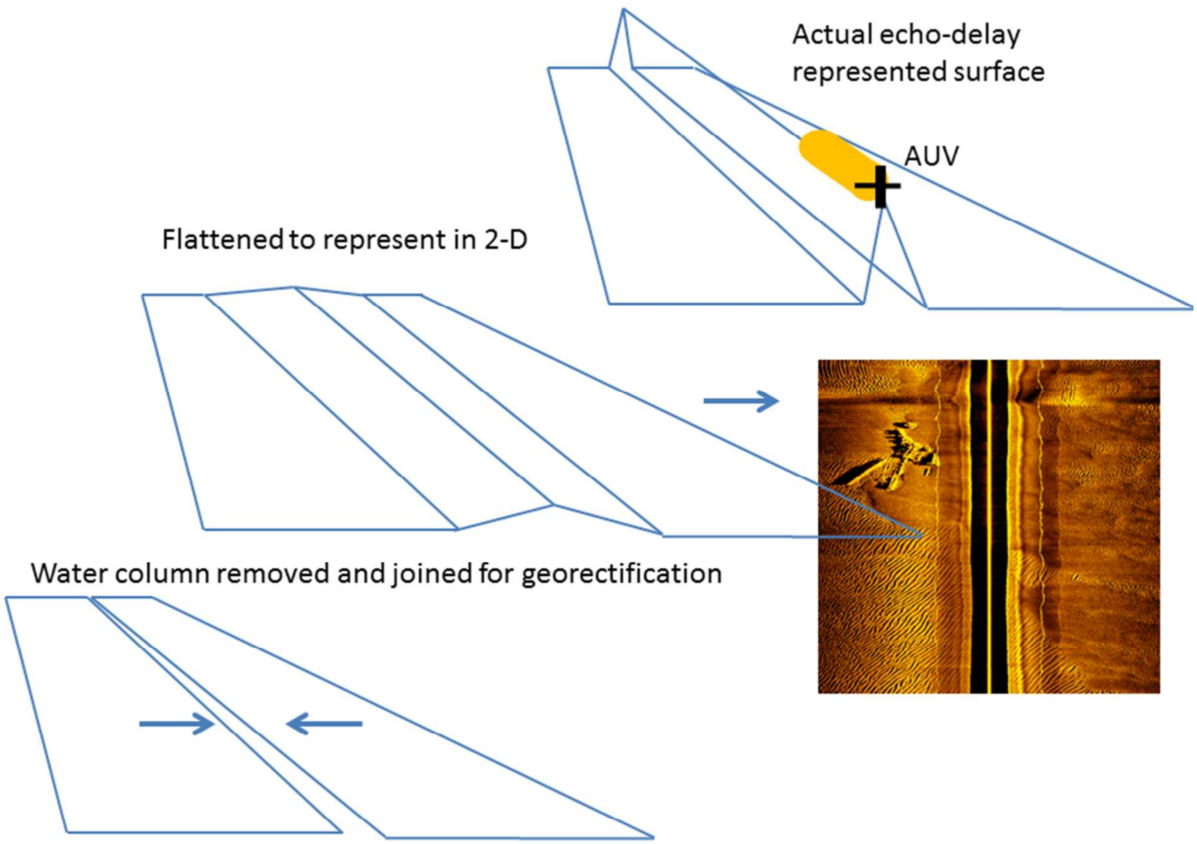

Actual echo-delay
represented surface
AUV
Flattened to represent in 2-D
Water column removed and joined for georectification

Figure 1.

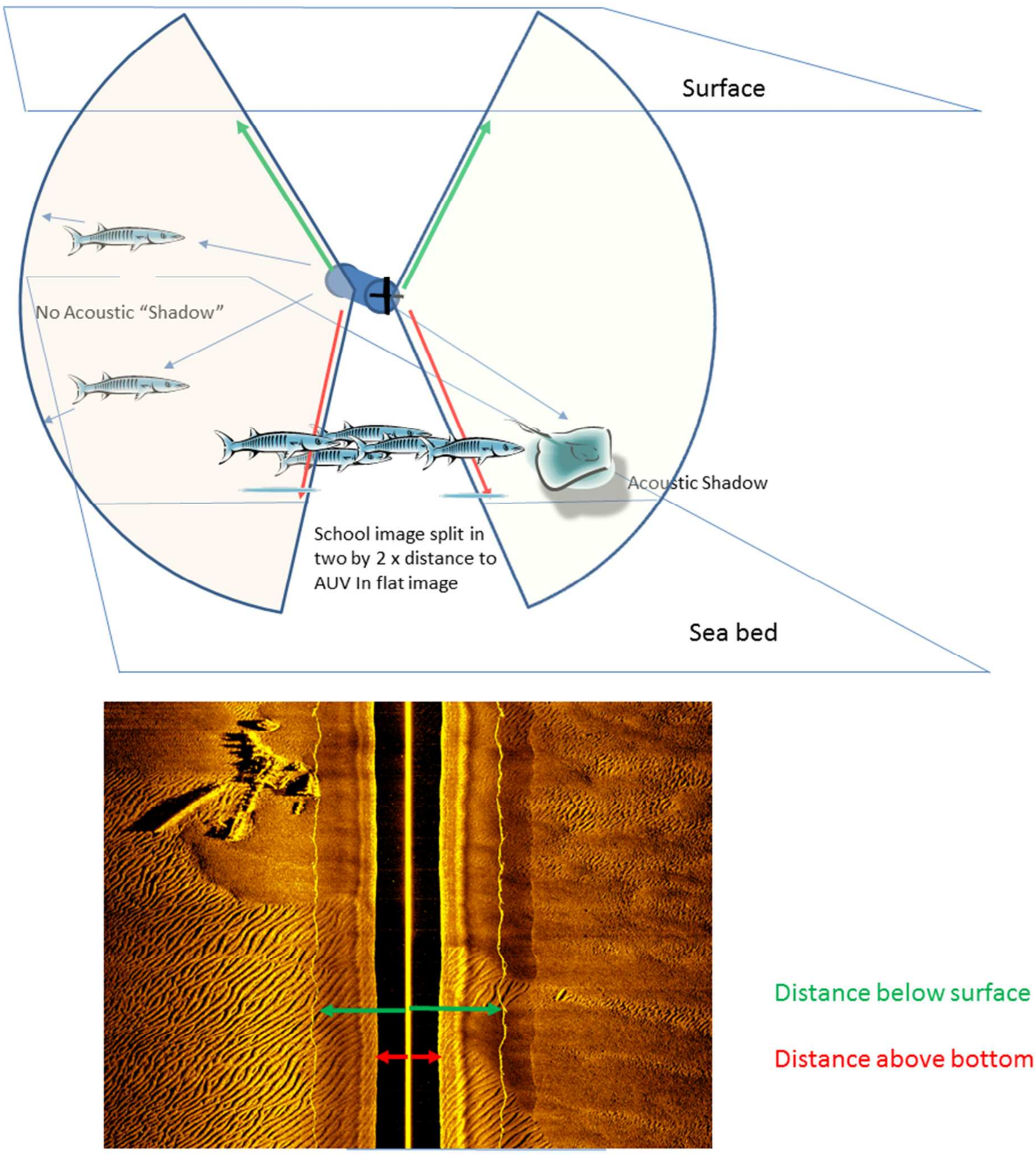

Surface
No Acoustic "Shadow"
Acoustic Shadow
School image split in two by 2 x distance to AUV In flat image
Sea bed
Distance below surface
Distance above bottom

Figure 2.

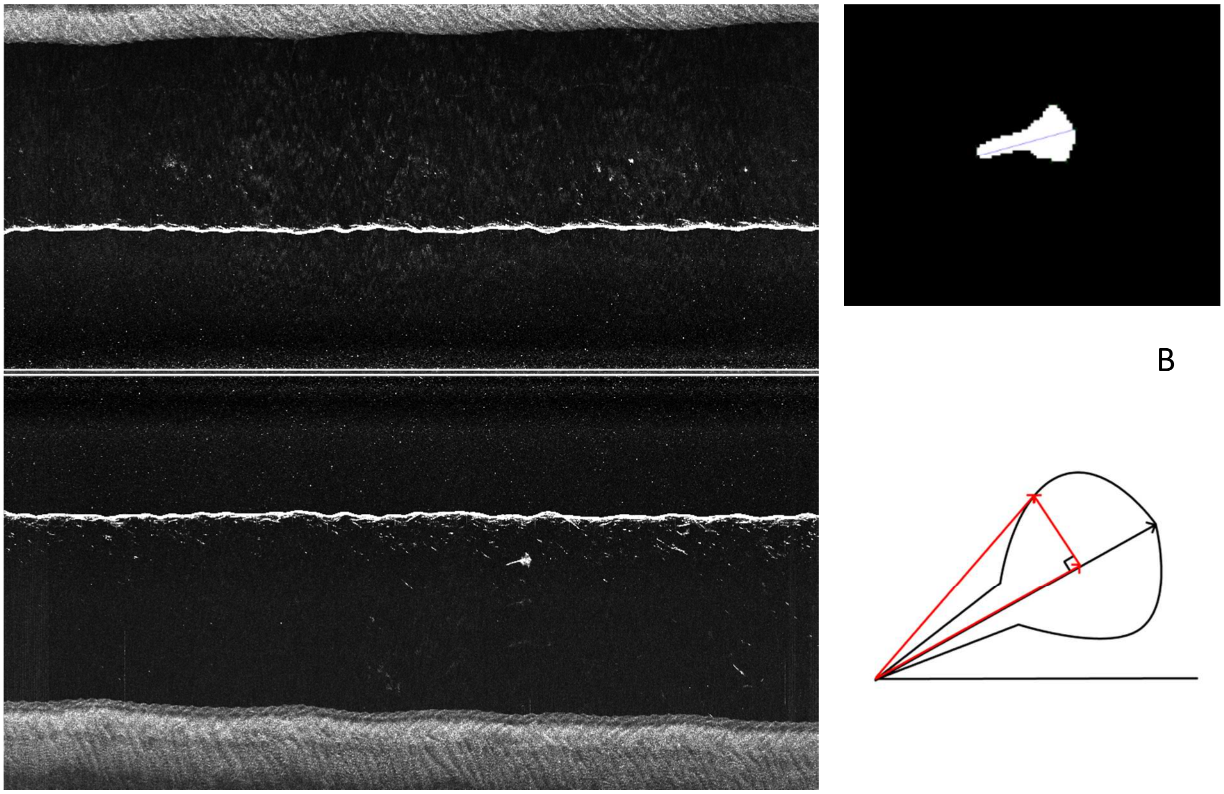
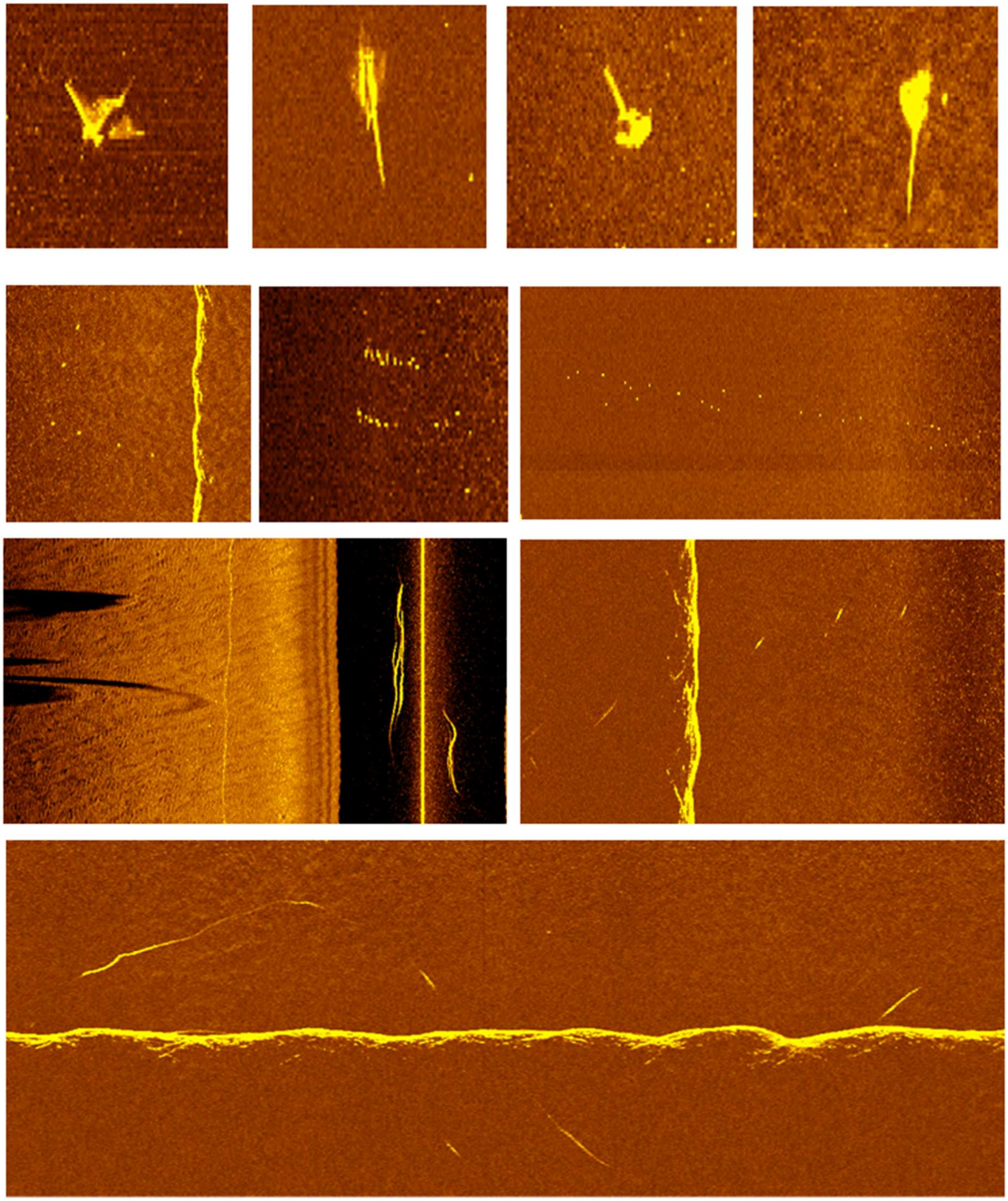


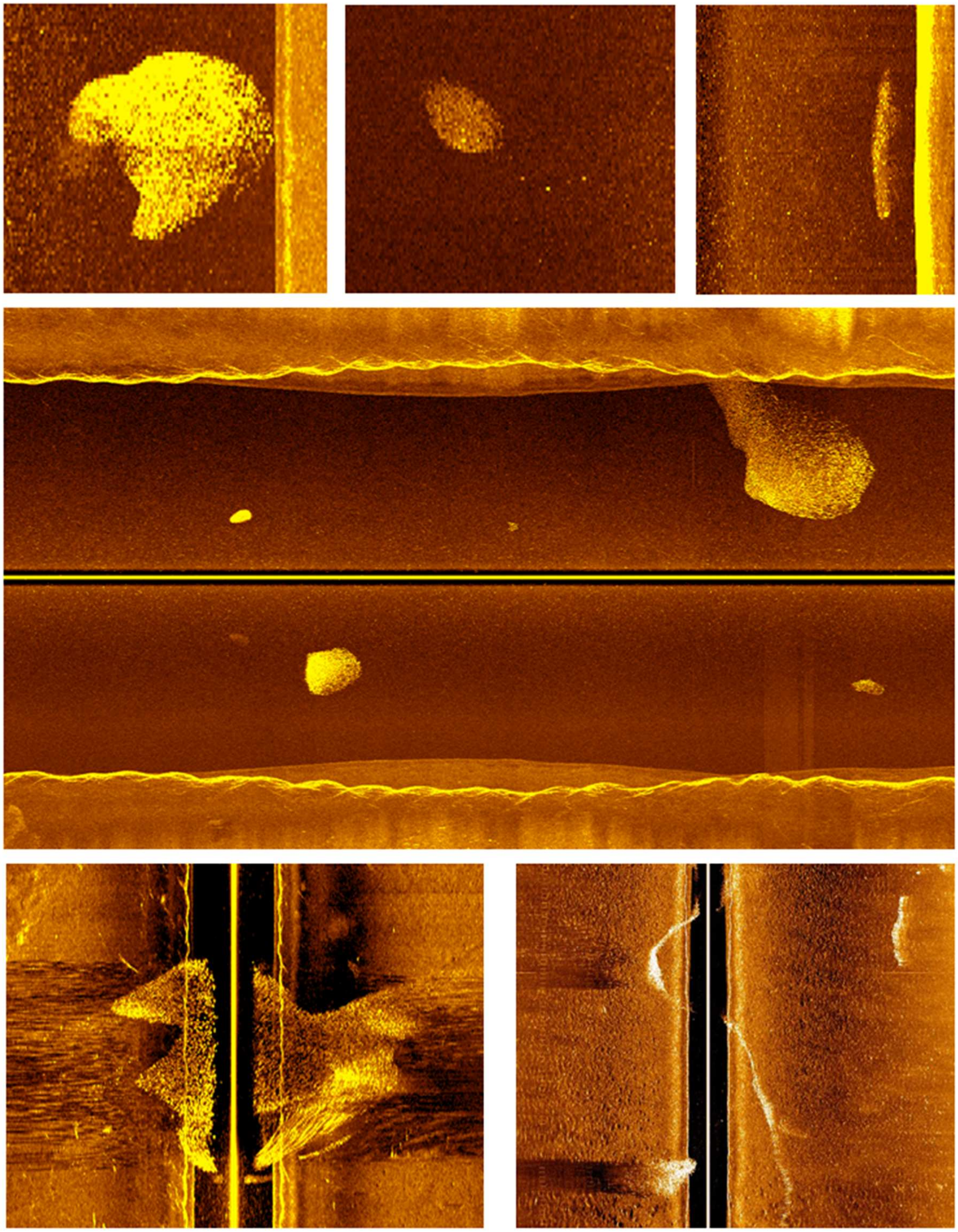
Figure 3.

1075



1076

1077 Figure 4A



1078

1079 Figure 4B

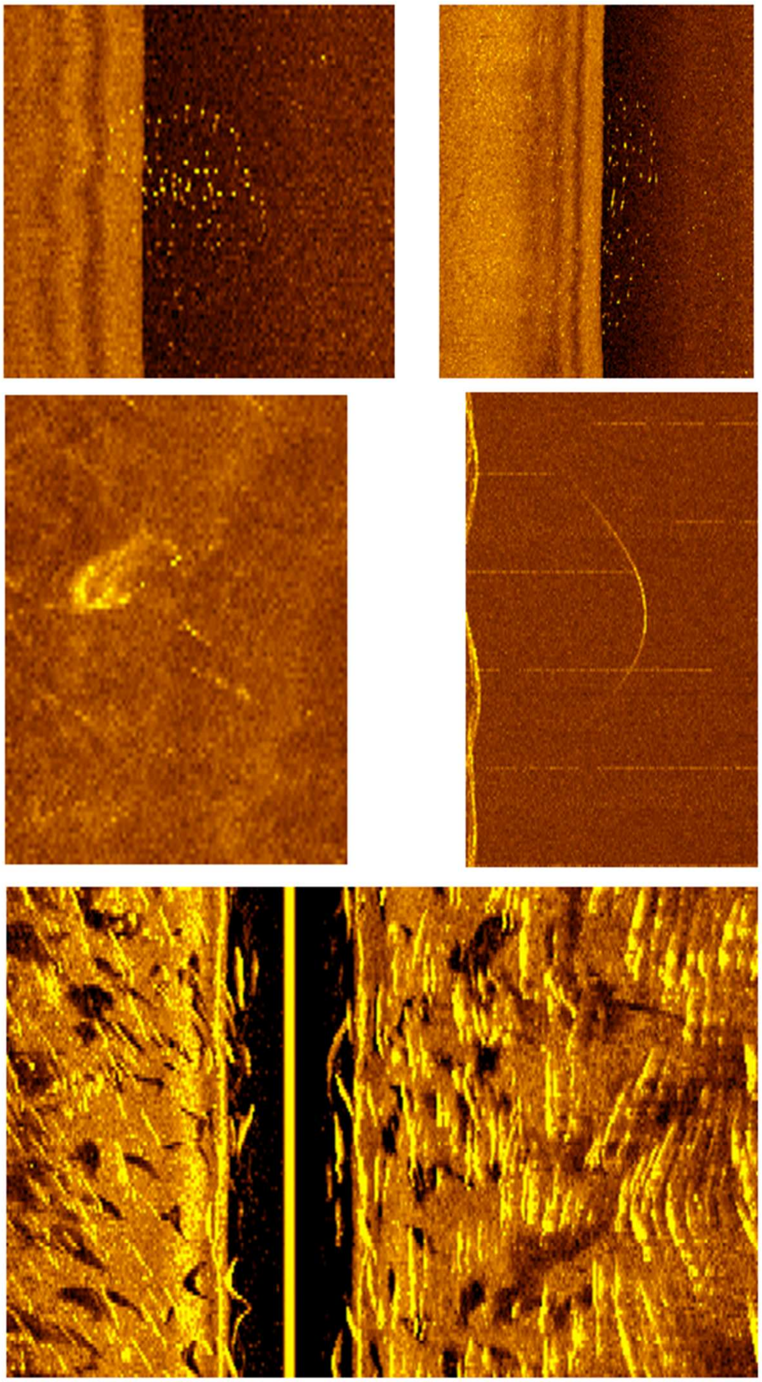
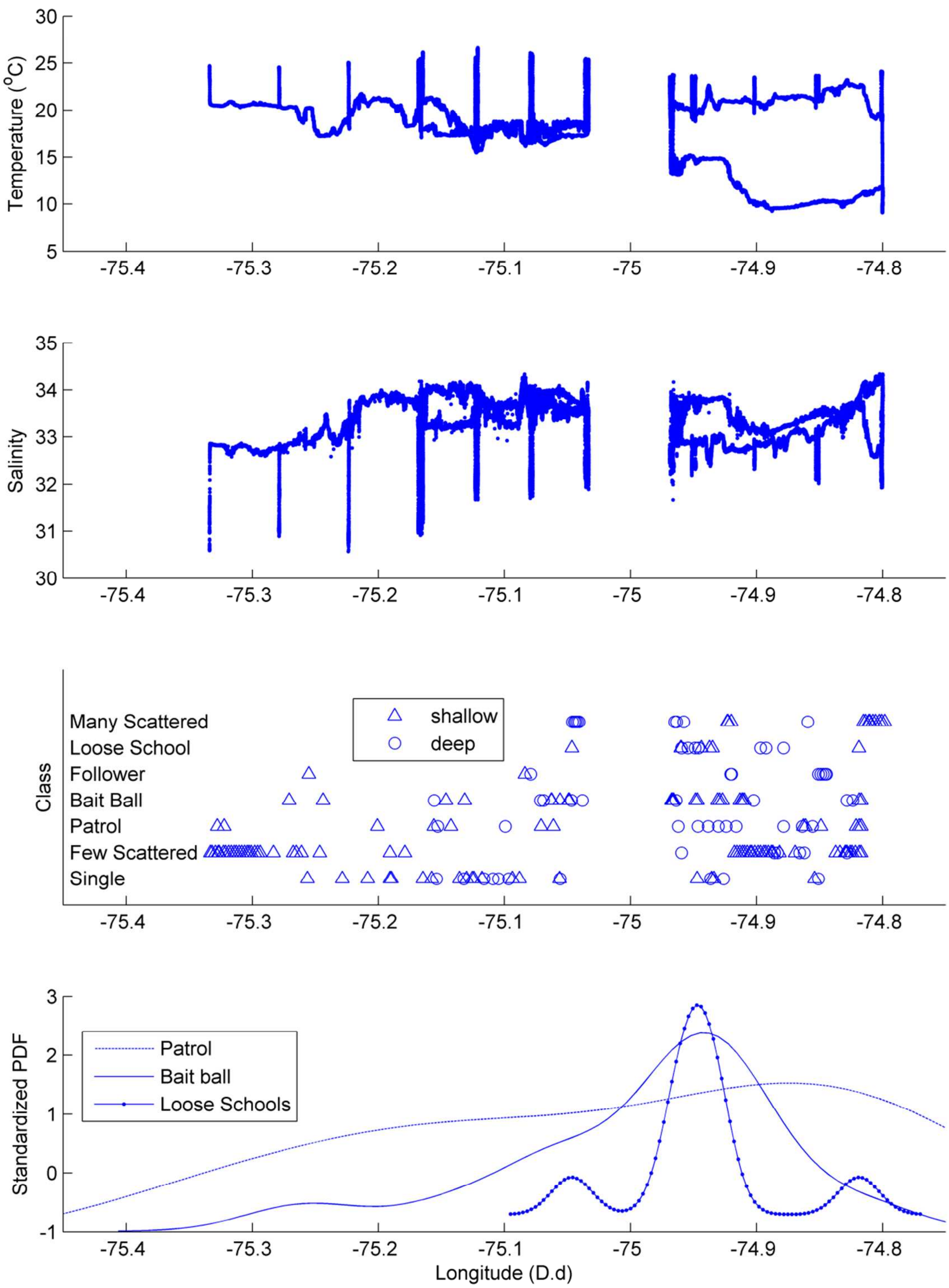


Figure 4C



1083

1084 Figure 5.

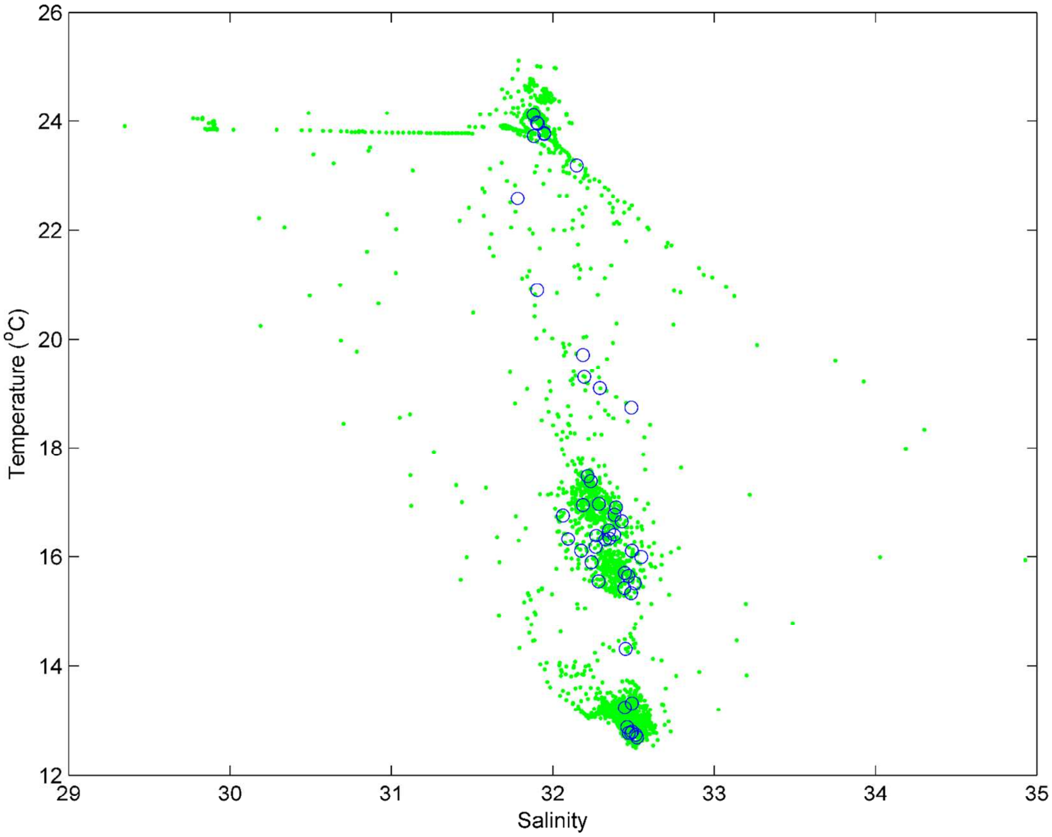

Temperature (°C)
26
24
22
20
18
16
14
12
29
30
31
32
33
34
35
Salinity

Figure 6.

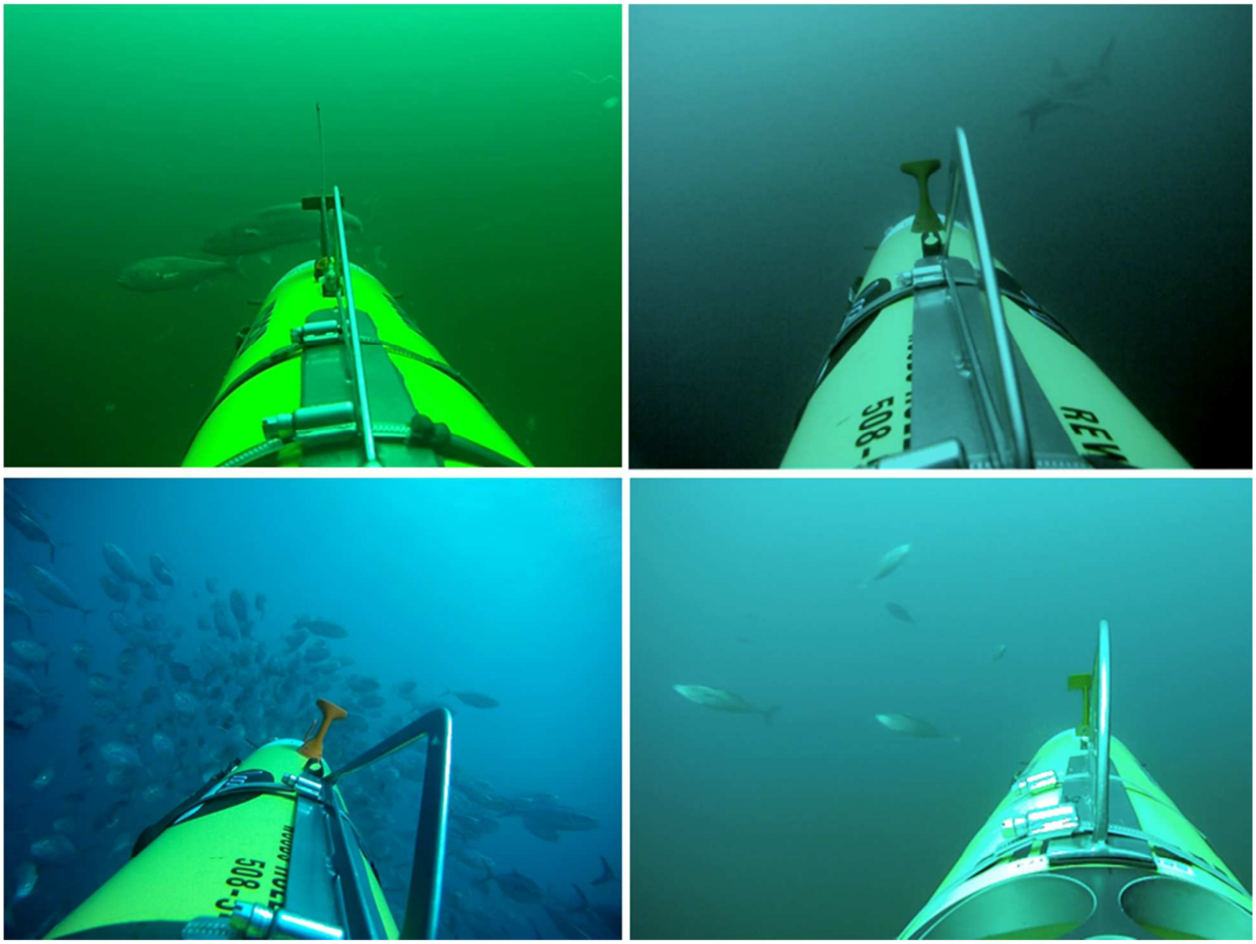


Figure 7