Broadband Active Sonar Swimmer Detection and Identification

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***Abstract*— This paper proposes a viable solution to the port security swimmer detection/identification problem using a broadband active sonar system with TCP/IP interface. Broadband active sonar, characterized by compressed pulse and wide-ranging spectral features, offers the ability to locate an underwater target accurately and classify it as a swimmer (diver) apart from fish or marine mammals, thus considerably reducing the false alarm rate compared with existing energy-based detection systems. Coupled with tracking algorithms, the fusion output detector can further reduce false alarms, allowing high-probability automatic alerts to security forces that can't continuously and consistently monitor this sector. Applications of conventional back-propagation algorithms or probabilistic neural networks in cooperation with track-based averaging technique show promising performance to this real-world classification problem. Several testing efforts conducted in both Alaska and Washington state waters have demonstrated the applicability of the technology and highlighted aspects of deployment around facilities such as ferry terminals and cruise ship docks for homeland security**

I. Introduction

Providing security for 361 ports and 12,383 miles of US coastline is becoming a more significant mission over time. This coastline is susceptible to both criminal and terrorist attack. Waterside facilities and critical infrastructure are especially vulnerable to attack from on- or under- water. It is getting more and more important to monitor underwater activities with proper equipment.

Advanced swimmer detection/identification systems have been designed for point protection of critical and/or high value assets for limited periods. There is a need for a low cost underwater threat detection system that can be installed for extended periods around a fixed commercial or civil asset.

Applications of broadband sonar technology and computational intelligence for underwater target classification have been studied by many fisheries biologists [1], [2], [4], [5], [7]. Especially, studies by Scientific Fishery Systms Inc. (SciFish) and Alaska Native Technologies, LLC (ANT) have shown promising performance to identify fish by species and by sizes as well as non-fish target localization, tracking, and identification [3], [6].

In this section, we would like to provide the background of broadband sonar signal processing, detection, classification, and tracking.

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A. Broadband Active Sonar

Advantages of broadband active sonar include broad spectral information, improved target detection, improved range resolution, and more stable estimate of the acoustic signal, which is justified by the following facts:

- *Broad spectral information*: Since spectral information is proportional to the bandwidth, broad spectral information is naturally achieved.
- *Improved target detection*: Target scattering strength varies strongly with frequency due to geometry, multi-scatterer interference, resonances, and elastic effects, etc, thus large fractional bandwidth is needed to observe these variations.
- *Improved range resolution*: Signal energy/noise power spectral density is the key detection statistic in noise limited situations and the range resolution is the key in reverberation limited situations. Large time-bandwidth product and pulse compression allow high energy with fine range resolution with ratio of 1/TB, where T is the transmit pulse length [s] and B is the band width [Hz].
- *Stable estimate of acoustic signal*: It is known that the narrow-band echoes suffer from Rayleigh fading where as broadband echoes are more constant because the broadband probability density function has less variation in intensity and less chance of echo intensity being near zero due to the Rayleigh fading.

B. Detection and Classification

The detection and classification systems are closely linked. Typical detectors are energy/threshold based, however *classify-before-detect* systems where the classifier is applied to all data have shown substantial success in detecting targets at low energy levels. The key to building a good classifier is to identify a set of features that can be extracted from the existing data sets, which should be computationally realistic and can separate the desired classes. For our application, there are two proposed classes, human swimmers and everything else.

C. Tracking Algorithms

The current riverine tracking technology is to manually track all underwater targets. However, manual tracking is very tedious and tracking by several technicians adds subjectivity and inconsistency. An automated tracking system will allow more targets to be tracked, reduce costs, reduce subjectivity, and add consistency.

We can split the tracking problem into two separate subproblems. One is prediction and the other is association. Prediction forecasts position and velocity at the next step.

Typical predictors include the α-β filter and the Kalman filter. Association assigns the predicted location to a detection - basically it assigns a new detection to an existing target track, or creates a new target track. Typical assignment schemes include nearest neighbor (NN), global nearest neighbor (GNN), probabilistic data association (PDA), joint probabilistic data association (JPDA), and multiple hypothesis tracker (MHT).

The α-β tracker is the combination of the α-β filter and a nearest neighbor assignment. This is an efficient tool for simple tracking of sparse target distributions without conflicting conditions such as crossing tracks. Due to its relative simplicity, implementation is straightforward. However, the MHT uses a multiple scan method. It postpones its decision making when the current assignment is uncertain until sufficient information is acquired in the following measurements. Both the memory and computational requirement increase exponentially with problem size [19], [20], [21].

II. Concept of ANT Swimmer Detection System

The ANT Broadband Active Multi-beam Sonar (BAMS) will be based on a broadband sonar system developed by Scientific Fishery Systems, Inc., and will utilize artificial neural networks for target classification. Its outstanding capability to discriminate underwater targets has been demonstrated in various applications giving over 87% correct classification of fish species. An earlier generation system was used in a Navy Coastal System Center swimmer detection demo conducted at Port of Brownsville (WA) in 2003.

To achieve the desired underwater coverage, ANT proposes using multiple transducers to cover the horizontal angular range, controlled by a single stand-alone system via versatile TCP/IP communication at the dry-end part of the system. The two components are connected by a multi-conductor cable that provides power and a hard data link between the 2 environments. Once the data is available to the dry end, it can also be made available on a secure web for remote monitoring. Fig. 1 shows a simple installation at a dock with 2 BAMS units mounted on pilings at a depth below the expected keel depth of any ship docking there. The data/power cables connect the units to a security center where the processed results can be displayed, or shipped to a remote connection either by wire or over Wi-Fi or wireless broadband connections. The security center can be a van, or a fixed building.

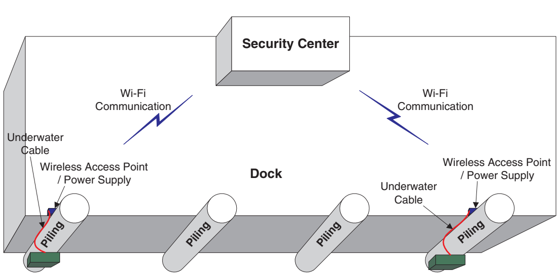

Fig. 1. A potential deployment scenario of BAMS systems.

An operator will have access to multiple sensors, potentially at several locations, via the web-based system Fig. 2 shows a candidate display with 6 units in use, one of which is displaying an alert (Unit 6). Since the automatic *track-and-classifier* minimizes false alarms, the primary display simply flags the location of a potential intruder to the sensor level, for example. A more careful examination of each sensor's output, both classification and track, can be called-up and displayed in another window by the operator. In fact, clicking on any of the unit icons will give the operator access to more detailed displays for either operation or maintenance.

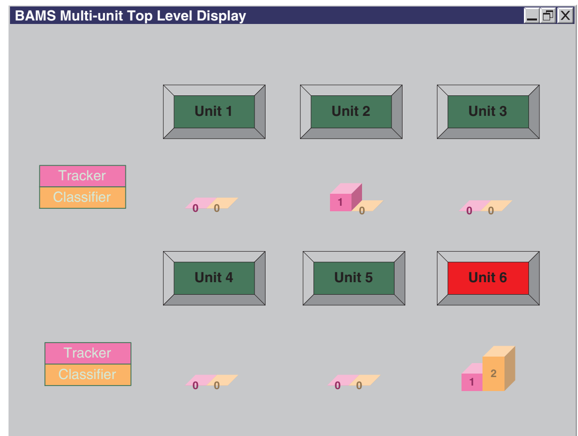

Fig. 2. Sample multi-unit top level display showing a detection on unit 6.

We envision the system to operate in a semi-autonomous mode, only alerting the operator when a swimmer is detected or there is a component failure that needs attention. This reduces operator workload, enabling a single operator to access this and other security systems simultaneously. Other than maintenance, there is no need for an operator to do anything but respond to an alert.

The BAMS is applicable to several types of vessel moorings, including along-side docks, nose/stern in to dock (similar to most ferries), and temporary installations. Remote, temporary installations may be powered by batteries on a buoy and in those instances the dry-end electronics will need to be located on the buoy and use wireless communications to ship the data to a shore-side operator viewing station.

Communication between the operator location and on-site security is essential. When an alert occurs, the operator can access screens that show the classification and track so that details can be relayed to the field security units.

III. Field Test and Data Collection

A series of field tests has been conducted to demonstrate the capability of the broadband sonar system to identify swimmers from other underwater objects, to exhibit the reliability of the system providing sufficient detection range under realistic environments, and to investigate practical operational concepts for site deployment. Four field tests were conducted: 2 lake tests at Marion Lake, AK, an overnight test in salt water at Port Ludlow Bay, WA, and a salt-water test at a ferry dock in Bremerton, WA near the Puget Sound Naval Shipyard. In the first 2 tests, classifiers were built and the data, both detections and classifications, are shown in the test result in the following subsections. The ferry test was conducted at the end of November and there was insufficient time to build classifiers, however interesting facets of the geometry of the site and normal operations of the ferry were observed that affect the deployment of the systems in those locations. These results are folded into our design.

A. *Test Procedure*

Two known targets (air filled 2-*liter* plastic bottles) were placed in the water column as reference. One was placed at 30m and the other was placed at 71m range. A swimmer started to swim from the 22m point toward the first bottle at 30m. After passing the first bottle, the swimmer went to the surface to adjust his swimming direction, and then swam straight toward the second bottle. The swimmer surfaced to re-adjust the swimming direction at 65m, and swam past the 2nd bottle up to 95m range until he started turning around to come back. The swimmer surfaced several times to re-adjust his direction when he was coming back.

We noticed a lot of air bubbles which were caused by the swimmer's kicking motion, especially when the swimmer was at close ranges as well as when he was on the surface. This had the effect of diminishing the separation between the swimmer and the air-filled bottles for the classifier, as the air bubbles were included, necessarily, with the swimmer echoes. The detection plots of this test procedure and a table of extracted data sets are found in Appendix.

B. *Echo Extraction and Principal Component Analysis*

Only small sections of collected data were extracted for spectral analysis. Approximately 200 echoes from the second bottle at 71m were compared with those of the swimmer at 63$\sim$70m range outward bound (flippers toward the sonar, generating bubbles). The extracted spectra within the frequency of interest (60$\sim$120 kHz) were converted into principal components.

Fig. 3 shows the two biggest principal components that provide the biggest separation between two types (swimmer and bottle). This technique is very useful to investigate the preliminary indication of separability among different targets in high dimensional feature space. Also, Fig. 4 presents the two biggest principal components when one more target was added for comparison. The PCA test looks very promising, because only a few principal components out of 60 distinct spectral energy bins even show the possibility of separation among different targets.

Since some degree of separation was observed between the swimmer and the bottle data, we anticipate that the artificial neural network will improve the discrimination between the two types, because (1) the artificial neural network utilizes the full degree of freedom of feature sets without data loss, and (2) the artificial neural network provides flexible non-linear separation.

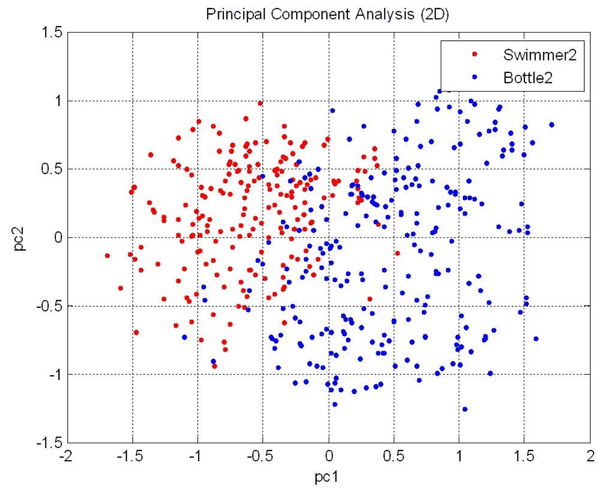

Fig. 3. Principal component analysis: 2-dimensional presentation of 2 different targets.

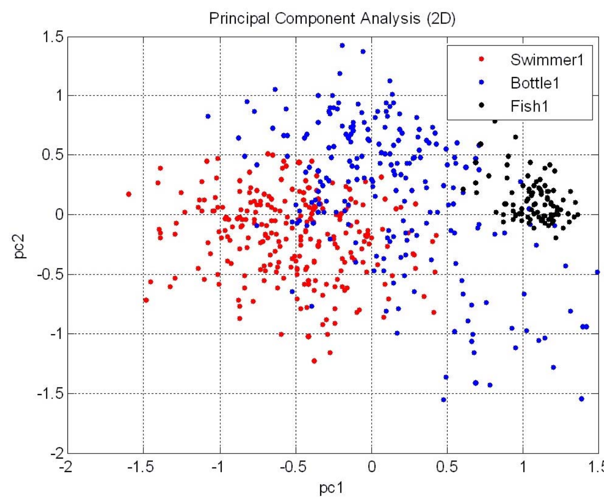

Fig. 4. Principal component analysis: 2-dimensional presentation of 3 different targets.

C. *Classification Performance*

After the visual verification of separability among different types, an artificial neural network was trained to build a classifier. In this example, a multi-layered perceptron was trained using 10% of the randomly extracted spectra from 2 different data sets, Swimmer1 and Bottle2, representing swimmer target and non-swimmer target, respectively (See Appendix for data collection log). The data set Swimmer1 was collected when the swimmer was on the surface of the water for adjusting the swimming direction and the data set Bottle2 was a part of transient air-filled 2-*litter* bottle detections.

The trained neural network was used to colorize the detections by types. The following plot (Fig. 5) shows the final classification run. The red detections represent the swimmer and the blue detections represent the bottle.

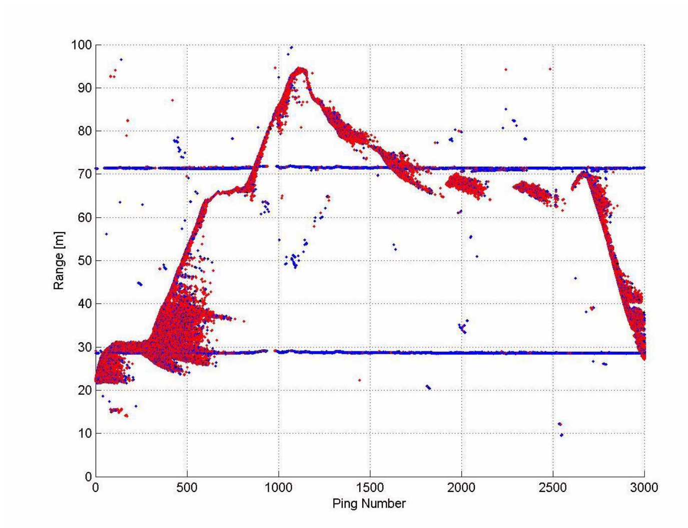

Fig. 5. Classification result for swimmer vs. bottles.

There are several lightly scattered misclassifications, but the overall track of the swimmer looks obvious as well as that of the bottle. In fact, this plot does not simply show the testing of the classification, but includes both training and testing. However, only a small fraction of the entire data sets provided very good generalization capability and the false alarm ratio could be significantly reduced compared with the conventional energy-based detection algorithms.

IV. Experiment for Track-Based Classification

In this section, we compare two approaches of neural network implementation to classify 4 different targets (bottle, bottom, fish, swimmer). The first neural network utilized individual echoes to train and test the classifier whereas the second neural network used the treated data sets averaged every 5 echoes (running average) within the same track.

A. *Classification from Individual Detections*

Individual spectral signatures from bottle, bottom, fish, and swimmer were used to train and test the neural network. The total number of echoes used for training is 518 (17%) and that of testing was 2,066 (83%) in this case.

Table I shows a confusion matrix explaining the performance of the neural network. For example, out of a total of 128 actual "swimmer" echoes, 81 echoes (63%) were correctly classified as swimmer and 31 echoes (24%) were incorrectly classified as bottle.

Fig. 6 shows a screen capture with annotation of the SciFish classification run. While the ping series is replayed, the classes are displayed in different colors. Bottle echoes at 12m were mostly colorized by yellow, swimmer echoes were mostly colorized by red, bottom echoes were mostly colorized by green, and fish echoes around the bottle ranging from 5m to 35m were well colorized by cyan except one track at 18m. Even though there were misclassifications during the test run, we can identify obvious tracks of major colors.

TABLE I

Confusion matrix for classification of 4 targets with individual detections.

	Actual Bottle	Actual Bottom	Actual Fish	Actual Swimmer	Total
Classified as Bottle	215	118	25	31	389
Classified as Bottom	3	992	38	10	1043
Classified as Fish	24	220	50	6	300
Classified as Swimmer	71	170	12	81	334
Total	313	1500	125	128	2066
True-pos. ratio	69%	66%	40%	63%	
False-pos. ratio	10%	9%	13%	13%	
True-neg. ratio	90%	91%	87%	87%	
False-neg. ratio	31%	34%	60%	37%	

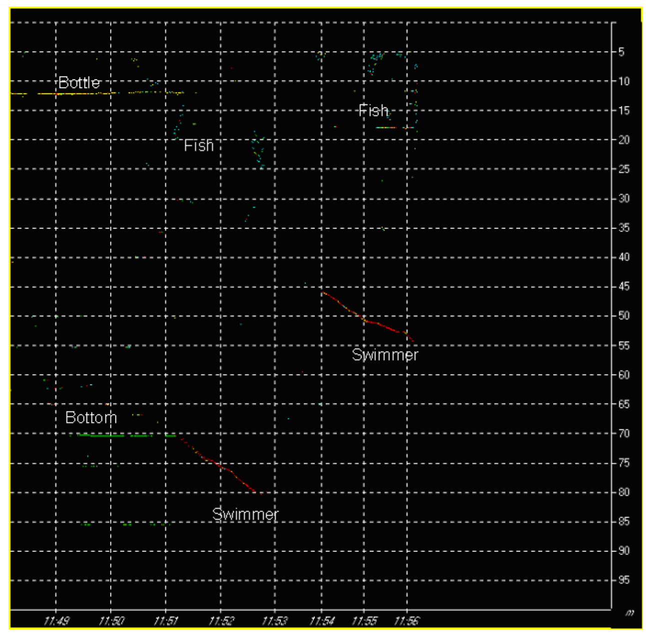

Fig. 6. Screen capture of the SciFish classification run for individual detections

B. *Classification from Track-Based Running Average*

In this approach, we extracted a few sets of tracks from the same two ping series resulting in nine different tracks over the four available tracks. Afterward, we computed a running average of 5 echoes for the spectra for each track, resulting in a reduced data set that represented theorized results of using a range only tracker in conjunction with the classification process.

The total number of echoes used for training was 150 (20%) and that of testing echoes was 609 (80%) in this case. The results jumped up to a range of 84%∼99% correct classification as illustrated in Table II below.

Fig. 7 shows a screen capture with annotation of the SciFish classification run. While the ping series is replayed, the classes are displayed in different colors. We can see some improvement over the neural network shown in Fig. 6. Bottle

TABLE II

CONFUSION MATRIX FOR CLASSIFICATION OF 4 TARGETS WITH TRACK-BASED RUNNING AVERAGE.

	Actual Bottle	Actual Bottom	Actual Fish	Actual Swim	Total
Classified as Bottle	287	2	0	19	308
Classified as Bottom	24	134	0	6	164
Classified as Fish	0	0	74	3	77
Classified as Swim	29	3	1	177	210
Total	340	139	75	205	759
True-pos. ratio	84%	96%	99%	86%	
False-pos. ratio	5%	5%	0%	6%	
True-neg. ratio	95%	95%	100%	94%	
False-neg. ratio	16%	4%	1%	14%	

echoes at 12m were mostly colorized by yellow, swimmer echoes were mostly colorized by red, bottom echoes were mostly colorized by green, and fish echoes around the bottle ranging from 5m to 35m were well colorized by cyan except one track at 18m. Although there were misclassifications during the test run, we can identify noticeable tracks of major colors, especially when we associate this result with the tracker algorithm and a single track's identification is obviously determined by the major distribution of classes within the track. For example, even if the swimmer track contains some misclassified echoes, the major class can be assigned in its track.

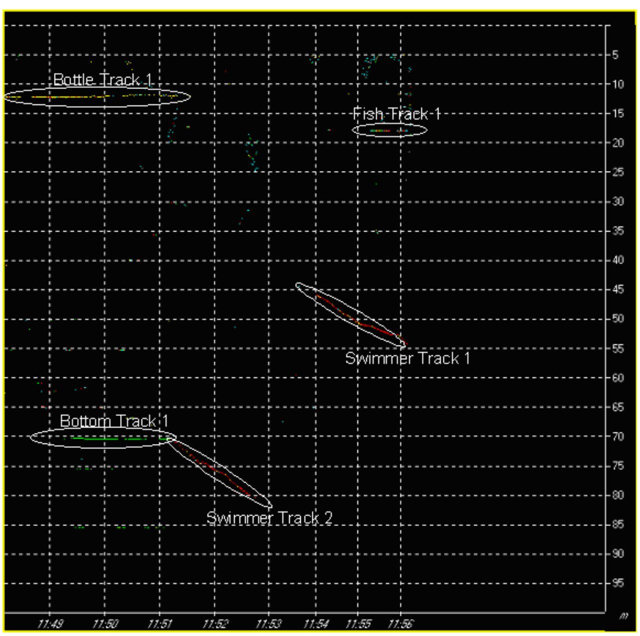

Fig. 7. Screen capture of the SciFish classification run for track-based classification

V. CONCLUSIONS

We described the detailed proposal for broadband, active, multi-beam sonar system for use as a swimmer detection system to protect marine port assets. This system is based on a 3rd generation commercial *off-the-shelf* fish-identification system that has been under development for over 12 years by SciFish from whom ANT will license the technology. Several tests have been conducted that demonstrated the applicability of the technology and highlighted aspects of deployment around facilities such as ferry terminals and cruise ship docks.

This concept BAMS system, based on the tests and analysis, should meet the general requirements of 1000 ft detection of a swimmer in port environments. The SciFish2000 series systems have historically identified fish to the species level at better than 85% correct rate. Coupling spectral classification with tracking algorithm further enhances identification and reduces the false alarm rate to allow automatic alerts to a remote operator. Since the system is web-based, a single operator can monitor multiple underwater units, or even physical locations, while also observing other alarm systems.

TABLE III

GENERAL DATA COLLECTION ANNOTATION FOR MARION LAKE (AK) TEST IN 2005

Type of Target	Ping Number	Range [m]
Bottle1	51:300	72
Bottle2	601:850	72
Bottle3	1160:1440	72
Bottle4	1160:1440	29
Bottle5	2680:2820	29
Swimmer1	51:300	29:32
Swimmer2	601:850	63:69
Swimmer3	1160:1440	78:91
Swimmer4	2680:2820	52:70
Fish1	200:350	3:4
Fish2	1160:1440	19
Fish3	2680:2820	26:27

APPENDIX

General data annotation is provided in this section. A table of extracted data sets is found in Table III and the detection maps of the field test at Marion Lake in AK are illustrated in Fig. 8, 9, and 10.

ACKNOWLEDGMENT

The authors would like to acknowledge that this work was supported in part by the U.S. Department of Homeland Security under Small Business Innovation Research Phase I Grant NBCHC050118.

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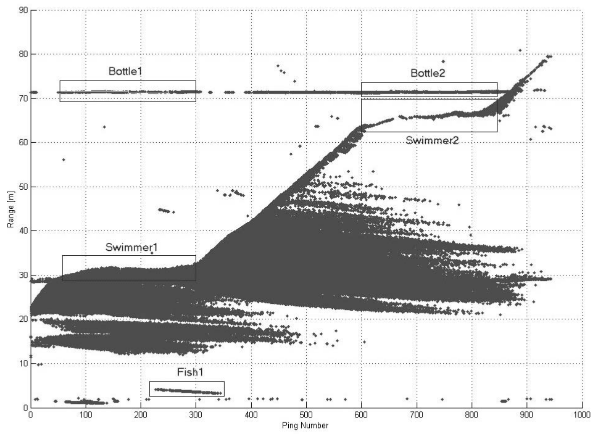

Fig. 8. Annotation of field data collection for the 1st 1000 pings.

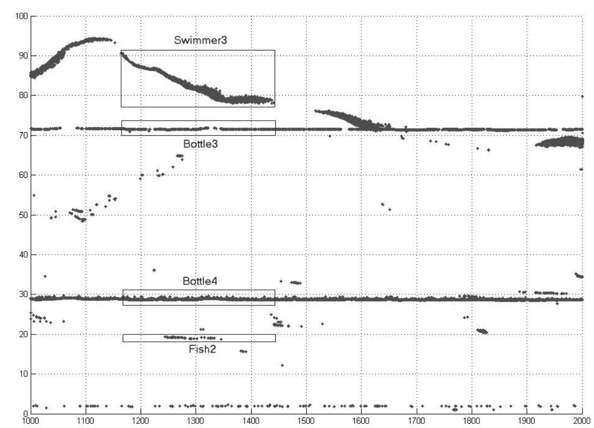

Fig. 9. Annotation of field data collection for the 2nd 1000 pings.

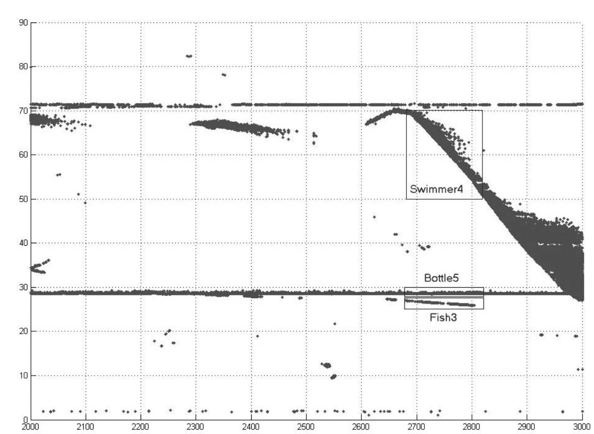

Fig. 10. Annotation of field data collection for the 3rd 1000 pings.

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