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Improved Surface Swimmer Detection through Multimodal Data Fusion

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***Abstract*—Waterborne intruder detection includes many new challenges not seen in land environments. One area of these challenges is the detection of surface swimmers. Swimmers, whose bodies are partially in air and partially submerged, have significantly reduced target strength (TS) for radar and sonar systems compared to intruders fully in air or fully submerged. This reduced TS results in more frequent missed detections or, if detection threshold is widened, increased nuisance alarms. Depending on sea state, a swimmer is also able to blend in with wave noise, making detection even more difficult. We present a method for improved surface swimmer detection in marine environments by fusing data from several sensor systems in both air and water domains to isolate a swimmer's signature from uncorrelated events. This system, tested in Dec 2011 in St. Petersburg FL, produced data indicating significantly improved detection over using any single system. By widening detection threshold of each sensor's detection algorithm but fusing data of each system together, more potential targets can be processed without the risk of increasing nuisance alarms. This work holds the potential to improve the security of several types of water-dependent assets, like commercial harbors, Navy or Coast Guard bases, and nuclear and other water-cooled power plans, and offshore oil platforms.**

I. Introduction

The goal of this paper is to analyze data from a test performed in December 2011. The purpose of the test was to configure multiple sensors in a marine environment with the ability to detect and track surface swimmers with the basic assumption that multi-sensor tracks may be used to enhance swimmer detection and tracking. The assumption was swimmer detection is difficult because of past knowledge from security advisors, and that the swimmer's profile occupies both water and air simultaneously producing a smaller target for above- and below-water sensors. The above-water sensor used was an ICX/FLIR 1400 radar and the below-water sensors were the Sonardyne multi-beam and the Biosonics single split-beam sonar systems. Prior to testing it was not known how these data sets were to be fused to improve the ability to track surface swimmers. The test was completely exploratory in nature, and prior to testing it was not known how well each individual sensor can track surface swimmers.

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II. Data Collection

Testing was conducted in St. Petersburg, FL at SRI International. The sensor systems utilized were the Sonardyne Sentinel Multi-Beam Sonar System, ICX/FLIR 1400 Radar, and Biosonics Split-Beam Sonar System. APL provided test direction on-site regarding the water sensors. APL and Sandia worked collaboratively to develop a useful test plan. APL provided a GPS system for tracking of the swimmers. Sonardyne and ICX/FLIR equipment was brought and operated by their respective employees. Biosonics was operated by test team members from Sandia and APL. SRI provided all facilitation services at their St. Petersburg, FL waterside facility.

Tests were conducted as follows with all three sensors running simultaneously and a simulated "asset" (floating dock) with sensors set up nearby. Refer to Figure 1 to obtain a map view of the designated runs.

- Track A: Perpendicular to seawall from asset, 75m
- Track B: Parallel to seawall across asset, 75m
- Track C_A: Farthest from seawall, 70m
- Track C_B: Second farthest from seawall, 70m
- Track C_C: Second nearest to seawall, 65m
- Track C_D: Nearest to seawall, 70m

Tracks in part C were on a diagonal line from the seawall, because that direction allowed the longest test distance while remaining in-harbor. Track length inconsistencies were due to rough placement of swim route markers by boat. Each track was swum by SRI swimmers between 5 and 30 times, depending on time constraints during tests on each of the three test days. Each "run" means one swimmer traveling the length of the track in any direction.

The segmented approach of Track C in the end was an effort to obtain sensor FOV at different ranges. It was noticed the A and B tracks were too close to the sensors and the C track was too far away. This was especially pronounced in the afternoon, when the ports sound velocity profile (SVP) made acoustic reflection at range impossible. In general, the port has excellent thermal mixing most of the year. In winter the water cools to approximately 70° F. On warm winter days the surface waters warm up in the afternoon creating a thermal layer on the surface and causing acoustic waves to bend away from the surface at range.

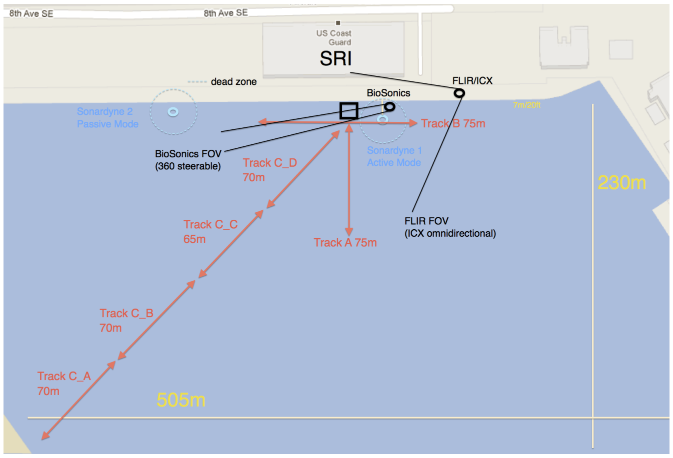

Fig. 1. Map of Test Run Tracks at SRI

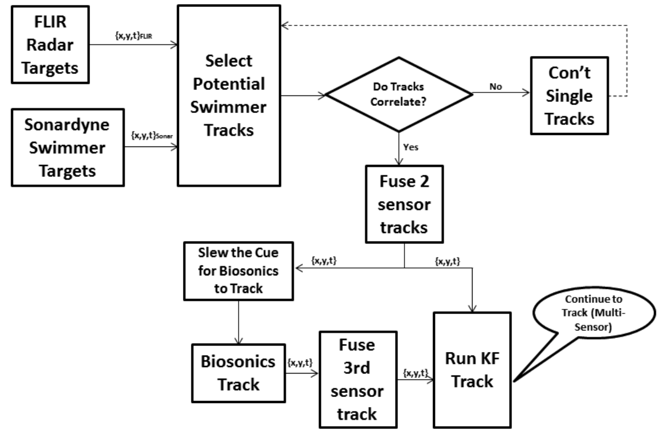

Fig. 2. Block Diagram of a Potential Multi-Target Swimmer Tracking Algorithm

III. Multi-Sensor Swimmer Tracking Algorithm

The data fusion problem for the set of sensors involves a level 1 fusion. All sensor data is used to assess the swimmer track from the track coordinates obtained from the sensor directly. The work here does not attempt to discriminate between NAR targets and real targets. The assumption is all targets moving at swimmer velocities on the surface are swimmers to be tracked.

Within this realm of tracking there are two distinct pieces of information that can be used to assess a track. The first is the logic that if more than one sensor is tracking a surface target with the same target coordinates the target is most likely a surface swimmer. This would be a heuristic rule for multi-sensor tracking. The second piece of information gathered from this testing is whether the multi-track data sets be combined or fused together to create an improved track on the target.

Certainly, many single sensor target tracking algorithms have been developed to demonstrate tracking. The results are well known; if one can increase the signal-to-noise ratio on target a more accurate track will result. Similarly, if multi-sensor tracking can be combined to produce a higher SNR the results will be similar. Data sets can potentially be collected to demonstrate these concepts.

The first method used was building a tracking state table. The goal of the table was to understand how the tracking data can be used to develop a data fusion tracking algorithm. Table I shows the state table for the three sensor systems.

The table shows all possible track scenarios for each sensor in the first three columns. In the case of no tracks, the assumption was made that a track already existed but lost on all sensor systems. In this case, a Kalman filter model could be used to continue the track until a sensor resumes the track. The state where only the Biosonics is tracking assumes the Sonardyne and FLIR lost previous tracks and the Biosonics maintains. The more expected tracks are where the FLIR and Sonardyne track together or separately and initiate a "slew the cue" to the Biosonics spotlight sonar system to begin a track. Ideally, all three are tracking and indicating a strong track.

The point of constructing this table is to help build the concepts for a robust data fusion algorithm with this data set. The table indicates that FLIR and Sonardyne tracks initiate the filter on rows 2, 3, and 4. Either the multi-beam sonar or the wide FOV radar will locate a potential target. The situation where both find the same target track then a hand-off to the Biosonics narrow-beam is initiated is indicted in state row 8. State rows 6 and 7 are similar with one sensor losing its track. The purpose of the diagram is to assist in the algorithm creation and also to yield more information about the track logic.

Next, figure 2 shows a generalized block diagram of a potential data fusion algorithm for this sensor suite applied to the swimmer tracking problem. The FLIR radar and the wide-beam Sonardyne sonar systems are used to survey the port area and look for potential swimmer tracks. Either system, or ideally both systems, identify a track. At the highest level, if both systems identify the same track then it is likely a target of interest and the coordinate information is handed off to the Biosonics system to initiate 'slew to cue and observe the potential track. With all three systems observing the same track, a Kalman filter is run using the combined track positions of all tracks. The attempt with this data is to show that a multi-sensor track yields an improved track with reduced error over a single sensor track. The potential advantages of the multi-sensor track are two-fold. First, all three sensors are observing the same track, reducing the possibility the target is a NAR or FAR significantly since all measurements are independent. Secondly, the multi-sensor track should yield a more accurate track. From the table above, reduced sensor inputs can still be used in conjunction with the Kalman filter. If only one or two sensors are tracking at any one time the filter uses that measurement with an increased covariance to track. If no sensors are tracking, the filter uses the model to maintain the track until sensor data becomes available.

TABLE I
BASIC DATA FUSION SENSOR TRACK STATE TABLE

FLIR Track	Sonardyne Track	Biosonics Track	Action FLIR	Action Sonardyne	Action Biosonics	Comments	Kalman Filter Action
0	0	0	None	None	None	No sensor sees target	Use model to predict
1	0	0	Initial track			FLIR Found Target: Expected Start of KF	Model with FLIR track
0	1	0		Initial track		Sonardyne Found Target Initially: Not expected but possible	Model with Sonardyne track
1	1	0	Initial track	Initial track		FLIR and Sonardyne found target: begin KF	Model with FLIR and Sonardyne track
0	0	1	Lost track	Lost track	Stays locked after hand-off	FLIR and Sonardyne lost target after hand-off. Biosonics still tracking.	Model with Biosonics track
1	0	1	Initial track		Hand-off to track	FLIR found target. Handed off to Biosonics track	Model with FLIR and Biosonics track
0	1	1		Initial track	Hand-off to track	Sonardyne found target. Handed off to Biosonics track	Model with Sonardyne and Biosonics track
1	1	1	Steady track	Steady track	Hand-off to track	FLIR and Sonardyne found target. Handed off to Biosonics track.	Model with all 3 sensors track

IV. DISCUSSION OF SENSOR TRACK RUNS

There were three sets of data runs recorded for all tracks: one set for the FLIR/ICX 1400 radar, one for the Sonardyne Multi-beam Sonar, and one for the Biosonics spot-light sonar system. An additional data set was recorded in conjunction with the radar: an infrared FLIR camera system to observe the radar tracks visually. This data was not processed as part of this work but remains an image processing-based option to increase sensor diversity.

As indicated the radar and the Sonardyne utilized vendor tracking algorithms to identify targets of interest and provide track data. In both cases the information lies in proprietary vendor software and the final tracks must be extracted from the vendor software. In most cases, this is not difficult but requires working with the vendor to obtain the track information.

We were able to work with FLIR/ICX to obtain the track information from the testing. The final data file included time and data pairs for all potential tracks recorded. Since all data was time correlated to UTC all tracks were aligned to the correct time. Position tracks were given in latitude-longitude coordinate pairs.

Unfortunately, the Sonardyne vendor data was not completed by the vendor in time to be incorporated into this analysis. Sonardyne plans to complete processing and deliver the data sets to Sandia in time to incorporate it into the presentation of this paper in October 2012. The Sonardyne data is discussed here but no results have been analyzed.

Finally, the Biosonics time and data pairs were extracted from the echograms recorded during testing. As will be discussed in detail, no tracker was available to track swimmer targets during testing and instead the tracks were inferred from echograms. This means they are not optimal tracks and did not involve active control feedback where the beam is steered to maintain optimal SNR and cross-hair track data. The tracks are a whitened best fit from the echogram data recorded during testing.

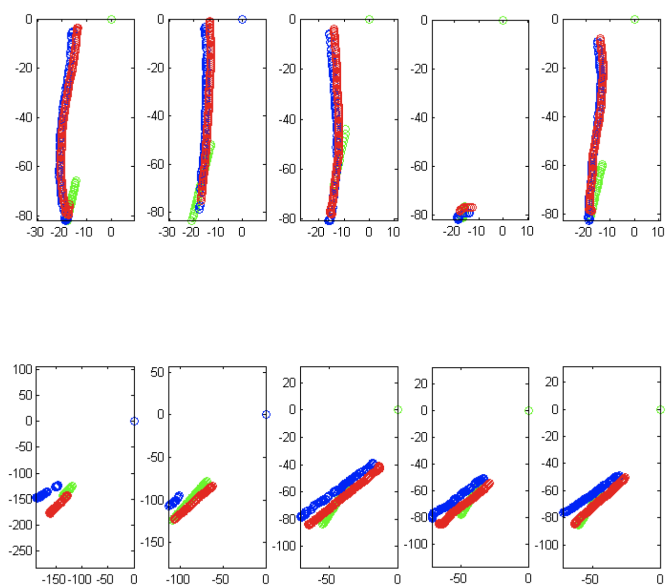

Fig. 3. Block Diagram of a Potential Multi-Target Swimmer Tracking Algorithm

From all the data recorded in the test, 10 tracks were studied because of the richness of data is each track set. These tracks are shown in Figure 3. The reason these tracks were used is all sensors identified tracks for these runs. Some of the runs are short-range and some are longer range tracks, and all provided useful track statistics to develop the Kalman filter.

V. SENSOR DATA ISSUES

One issue of concern through all tested sensors was a lack of optimal algorithms developed to track surface swimmers. As a result, the data presented is not necessarily the optimal set needed to solve this problem. The measured mean errors and covariance errors are likely higher and do not reflect the best that can be done with this suite of sensors.

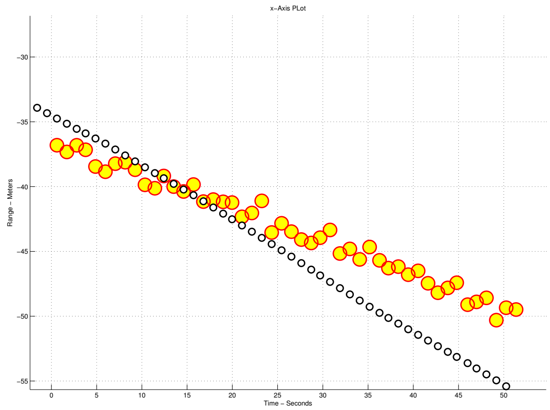

Fig. 4. Biosonics and GPS Track of swimmer demonstrating no Biosonics tracking.

This was very evident for the Biosonics narrow-beam sonar sensor. Biosonics has developed a robust underwater scuba diver tracker making use of the split-beam phase signal to keep the target in the center of the beam crosshairs by XY-motor gimbal adjustments. Unfortunately, for this testing the algorithm thresholds could not be adapted to accommodate swimmers. To compensate for this, the beam was manually steered in the direction of the diver swim path prior to the run with hope the diver would swim through the beam during the run. Because of the nature of the narrow 6-degree beam, most runs were either run to/from the sensor most of the runs could be captured in the beam.

The issue resultant issue was that the target was not focused into the center of the target but instead simply passed through the beam. As depicted in Figure 4 below, the Biosonics tracks (red with yellow centers) run diagonally through the GPS target track (black circles). Early in the track they lie skewed below the target track and at the end of the track they lie above the target, instead of the beam angle steering along to follow the progress of the target. This lack of tracking algorithm corrupted the statistics for this sensor.

VI. Multi-Sensor Data Fusion Using Bayes' Theorem

Although it isn't yet possible to numerically analyze most of the collected test data, there is information about the sensors and the tracking scenario to begin building an algorithm using this sensor suite for swimmer tracking using Bayes' Theorem:

$$P(X|Z^n) = \frac{P(Z^n|X)P(X)}{P(Z^n)}.$$

X is the target state (position) and Z is the sensor measured positions for multiple sensors. It is important to realize that each sensor is measuring a target position in time as the target moves along the path. The sensors' ability to track a target has a probability density function with a probability of detection and a probability of nuisance alarm rate. It can be assumed

TABLE II
Analyzed Covariance Statistics from Test Track Data

	cov $<$ 100 M	100 M $<$ cov $<$ 200 M
Biosonics Statistics	5.71	17.6
FLIR ICX Statistics	0.68	11.14

these functions and rates are different for each sensor system since the measurements are independent of each other but correlated by measuring the state of the track.

In our case, we know certain characteristics about each sensor that can be applied here without actually knowing the true probability density functions. The wide area radar system has much higher detection capability than the Biosonics narrow-beam sonar system. This can be determined by the track data and knowing that radar has a wide coverage area compared to the Biosonics system and overall improved sensor resolution. Also, it can be inferred that the Biosonics has much lower nuisance alarm rate (NAR) than the FLIR radar. Therefore, by fusing the FLIR and the Biosonics tracks an advantage is gained from the high detection probability of the radar with the lower NAR of the Biosonics. This use of data fusion is range-independent but takes advantage of both systems' attributes.

To quantify this result would require more extensive testing and data analysis. Each sensor would need to be characterized for probability of detection and nuisance alarms. Afterwards an analysis of fusing similar tracks from the three sensor systems will numerically demonstrate the overall advantage of having multiple sensors on target. At first pass, a the FLIR-Biosonics combination indicates a clear advantage using Bayes' Theorem to combine sensor tracks.

VII. Sensor Statistics Obtained from Data Tracks

Statistics were calculated from the tracks of interest to begin to see how the tracks can be combined to create a more accurate track of the swimmer target using multiple sensors. The Sonardyne tracks remain unprocessed at time of writing, so there were 3 track sets to work with: GPS, ICX/FLIR, and Biosonics. The GPS was considered the ground truth data and, though not without sensor noise, expected to be more accurate than the other two sensors. This comparative accuracy was especially pronounced at range as the FLIR and Biosonics beams both widen.

Results of the covariance analysis are listed in Table II. The calculations were made given point-to-point distance and not broken down into XY coordinates. In general, covariance results seemed correct because the near tracks had smaller covariance numbers than more distant tracks. However, it did appear that the numbers did not necessarily coincide with theoretical predicted covariance. The ICX/FLIR covariance for distances less than 100-M appeared to be correct; when discussing with the vendor, they expect a covariance of 1 to 2 meters. Secondly, the Biosonics covariance appears high at distances less than 100-M and moderate at distances greater than 100-M.

Ideally, these numbers could be compared to a theoretical covariance number. However, for the sensors specified the number are difficult to determine since the errors for both the sonar and radar increase linearly as beam-width extends outward. It is difficult to make a fair comparison although the covariance determined here rivals the theoretical covariance depending on where the calculation is made. Example at 100-M the theoretical covariance is expected to be 7 and the computed is 5.71. This makes some intuitive sense because the number comes from all data at distances less than 100-M.

VIII. Fused Data Kalman Filter Track Compared With Single Sensor Kalman Filter

Results here support the theory of Kalman filtering and data fusion. A Kalman filter selects an optimum track between the sensor measurement and a model of the swimmer assuming sensor noise and model noise. All noise is considered to be band-limited Gaussian white noise for the sensor and the state of the system model. The filter makes the best estimate using least squares criteria. It also uses Bayes' theorem to support the concept that each new sensor measurement is independent of the all previous, but correlated in with the state information of the swimmers velocity and position.

It has been demonstrated that by fusing sensor data sets having Gaussian distribution noise properties the variance properties can be combined to produce a reduced variance. Using Bayes' theorem the fused sensor variance becomes the parallel combination of the individual sensor variances, or:

$$\sigma^2_{fused} = (1/\sigma^2_{sensor1} + 1/\sigma^2_{sensor2} + 1/\sigma^2_{sensor3})^{-1}.$$

The result is an improvement in the measurement by fusing the data and allowing filtering to do a better job.

This information was applied to the a swimmer-tracking Kalman filter simulation using the noise covariance as measured from testing and applying the principles discussed. The results show that as the swimmer moves further from the sensor systems which increases the measurement covariance, data fusion-based Kalman filtering allows for more accurate tracking.

The figure below shows a simulated Kalman filter track for one run. We used the high covariance, 17.6, for the measurement to show the filter improvements. From the simulation the RMS error between the real track and the filter predicted track can be compared. Results of all simulations are shown in Table III.

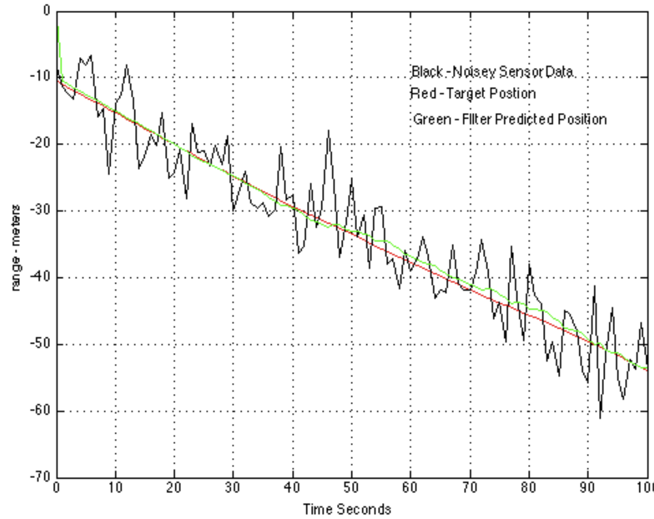

Fig. 5. Simulated Kalman Filter Track of a 0.5 m/s Swimmer with Noisy Sensor Data

TABLE III
RMS Error Results of Single Sensor Versus Fused Data Runs. (Regular font calculated, projected results italics)

	<100 M RMS Track error	> 100 M and <200 M RMS Track error	> 200 M RMS Track Error
Single Sensor	1.2m	1.9m	*2.2m*
Fused two Sensors	1.2m	1.2m	N/A
Projected 3 Sensors Fused	*1.2m*	*1.2m*	*1.25m*

IX. Conclusions

A multi-sensor swimmer tracking system was investigated to better understand a data fusion problem with potential real-world applications. One radar system and two sonar systems were used to track surface swimmers simultaneously. This proof of concept investigation used real data and real sensors. There were two important results: (1) it was found that is it always useful to put more sensors on target to improve detection, this may not accommodate tracking purposes, and (2) multi-sensor tracking using this sensor suite can begin to improve tracking accuracy at ranges over 100-M using data fusion and Kalman filter. Inside of the 100-M the data shows that any single sensor can track swimmer targets accurately.

To continue work in this effort, more testing and development must be performed to improve the statistics and results. All systems must first have fully-developed tracking algorithms prior to testing. In addition, the results presented here may be more useful if tests were performed at ranges of 150 to 350-M, or out to the detection envelope. This extended range is where data fusion may demonstrate the most usefulness. Finally, once each sensor has a fully developed tracking algorithm a complete swimmer detection and NAR test should be executed. This will fully characterize the sensor system over the port ranges allowing quantification of Bayes' theorem for placing more sensors on target.

Acknowledgments

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