Tracking of a Tagged Leopard Shark with an AUV: Sensor Calibration and State Estimation

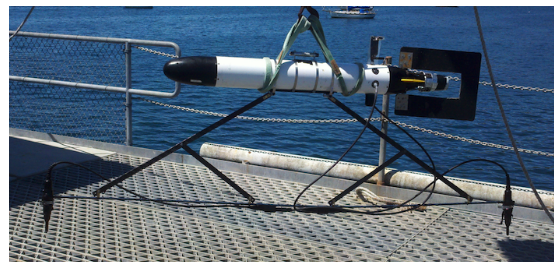
Forney, C. Manii, E. Farris, M. Moline, M.A. Lowe, C.G. Clark, C.M.

Abstract— **Presented is a method for estimating the planar position, velocity, and orientation states of a tagged shark. The method is designed for implementation on an Autonomous Underwater Vehicle (AUV) equipped with a stereo-hydrophone and receiver system that detects acoustic signals transmitted by a tag. The particular hydrophone system used here provides a measurement of relative bearing angle to the tag, but does not provide the sign (+ or -) of the bearing angle. A particle filter was used for fusing these measurements over time to produce a state estimate of the tag location. The particle filter combined with an active control system allowed the system to overcome the ambiguity in the sign of the bearing angle. This state estimator was validated by tracking both a stationary tag and moving tag with known positions. These experiments revealed state estimate errors were on par with those obtained by manually driven boat based tracking systems, the current method used for tracking fish and sharks over long distances. Final experiments involved the catching, releasing, and autonomous AUV tracking of a 1 meter leopard shark (*Triakis semifasciata*) in SeaPlane Lagoon, Los Angeles, California.**

I. INTRODUCTION

Though sharks have been widely researched, there is much to be discovered about shark behavior and movement patterns. In order to increase this knowledge, an autonomous mobile tracking system has been created which will provide researchers with the long term data that has been missing.

Current methods for tracking sharks include remote sensing GPS tags, manual active tracking, and stationary receivers (passive tracking). GPS tags provide accurate positional data, however, these data can only be transmitted when the shark is at the surface [13]. This leaves a gap in information on the location of the shark while not at the surface. Researchers can actively follow sharks with a boat using a mounted receiver; however, this requires human operation to navigate the boat to maintain a signal reading of the tag, and the position of the shark [9] so tracks are limited on temporal scales of hours to days. Finally, stationary acoustic receivers can gather data on the movement of sharks in a localized area. However, these are cumbersome to set up, and when the sharks move out of the range of the stationary receivers, data can no longer be recorded.



(a)

(b)

Fig. 1: The Iver2 AUV equipped with a stereo-hydrophone system is shown in (a). The species of interest, a Leopard shark is shown in (b).

Groups of acoustic receivers can be organized so there are many receivers spread over a specified area, either in high concentration in smaller areas, or wide-spread with receivers set up as gates to track the inward and outward movement of sharks and other tagged animals [3]. Unfortunately, none of these solutions address the problem of obtaining high spatial resolution positions on highly mobile species that may easily swim beyond the reaches of a stationary acoustic receiver.

In [5] the necessity for en-route decision making in AUVs was identified as a problem that needed to be addressed. AUVs have been programmed to follow a designated GPS waypoint path, recording information as it travels. Prior to this project, there had yet to be an AUV that could continually follow a single tag on a specific animal (shark) and make logical decisions on the changing location to follow the animal. An active localization of the shark is necessary to track and follow it as it moves. A major part of this active

C. Forney and E. Manii are with the Department of Computer Science, California Polytechnic State University, San Luis Obispo, CA 93405, USA cforney@calpoly.edu, emanii@calpoly.edu

M. Farris is with the Department of Biological Sciences, California State University, Long Beach, CA 90840, USA mfarris@csulb.edu

M.A. Moline is with the Faculty of Biological Sciences, California Polytechnic State University, San Luis Obispo, CA 93405, USA mmoline@calpoly.edu

C.G. Lowe is with Faculty of Biological Sciences, California State University, Long Beach, CA 90840, USA clowe@csulb.edu

C.M. Clark is with the Faculty of Computer Engineering, California Polytechnic State University, San Luis Obispo, CA 93405, USA cmclark@calpoly.edu

The authors gratefully acknowledge the contribution of National Science Foundation for funding this project.

localization is the sensor fusion required for such state estimation. The AUV was equipped with a stereo-hydrophone receiver system which provided differential time of arrival data necessary for state estimation. This paper presents a Particle Filter based method for fusing measurements from the stereo-hydrophone receiver over time, enabling real-time estimation of the shark state.

The paper is organized as follows. Section II discusses related works and elaborates on existing research. The problem definition is described in Section III. Section IV describes the state estimator, and breaks down the steps of the proposed algorithm. Experiments are described in Section V, and Section VI reports the results of these experiments. Section VII concludes the scientific contributions made by this project. Finally, Section VIII discusses future work to be done to further advance research in this area.

II. RELATED WORK

Current tracking of aquatic animals includes stationary receivers, receivers on boats, and GPS tags. Stationary receivers can track tag information while multiple tagged individuals are within range. However, once the animal leaves the area where the receivers are positioned, no data can be gathered. This is problematic for both stationary locations near the coast, as well as out in the ocean [3].

GPS tags provide a longer term solution, as they provide data consistently and are not restricted to a single area. However, once the shark dives below the surface of the water, the GPS signal can no longer be detected [13]. Ship-bourne receivers and directional hydrophones have been used by humans to steer the boat with the goal of following the tagged shark. However, boats can disturb the sharks and potentially change the behavior of the shark. In addition, this requires the human to maintain operation of the vessel and follow the signal of the shark for the length of the track.

Using robots to track and follow moving objects in itself is not novel. For example, there have been several projects developed to accomplish dynamic tracking systems based on vision. In [7], joint probabilistic data association filters are used in conjunction with particle filters in order to track multiple humans inside a building, and are able to successfully and reliably keep track of multiple persons [7]. The joint probabilistic data association filter is an algorithm that improves the separation and individual identification of data when tracking multiple objects. This particular study compares the success of Kalman filters to the success of particle filters when tracking a moving being. An additional study [8], also used particle filters and joint probabilistic data association filters to determine the location of people in an office type environment. Similarly, in [12] visual data is acquired by the robot in order to determine it's desired movement path. That particular study focused on soccer playing robots which need to track the location of a soccer ball in-order to determine their next move. In [7], a particle filter algorithm is used to predict the location of the ball.

Underwater robots have also been equipped with vision systems to track moving objects [2]. While in [14] a vision system was developed to conduct tracking of fish with an ROV, it was not implemented for autonomous tracking experiments. In [6], a vision system was used to successfully track jelly-fish with an ROV. AUVs have been equipped with acoustic receivers to passively record acoustic tag signals. In [4] an AUV was used to gather data from two tagged Atlantic Sturgeon in the Hudson River. This study proved that AUV's are highly useful in gathering data on a tagged fish. In [5] validated the use of hydrophone's mounted on a moving AUV.

Determining position of a tag from such acoustic measurements requires state estimation and filtering techniques. Kalman filter algorithms are often used in estimating the state in robot localization problems. Based on a distribution of error, Kalman filters use uni-modal Gaussian distributions for representations of state. Kalman filters are very efficient when used for localization[10], but due to the limitations of the uni-modal distribution, are best used when the initial position of the robot is known [1]. Another approach to robot localization is Monte Carlo Localization (MCL), a computationally efficient localization algorithm with the ability to represent arbitrary distributions [1]. MCL uses an adaptive sampling mechanism in which the number of sample states is chosen as the robot travels. A larger sample set is used when position is relatively unknown, and thus, MCL can globally localize a robot [1]. Particle filter estimation is heavily based on the MCL algorithm [10]. A particle filter state estimation algorithm approximates a belief state through a set of particle representations [11]. Each particle represents a single randomized representation of state, the set of which creates a multiple hypothesis sample set. In this paper, the particle filter's ability to handle ambiguous sensor measurements is leveraged to deal with a stereo hydrophone and receiver system that cannot determine the sign of the relative angle to a detected fish tag.

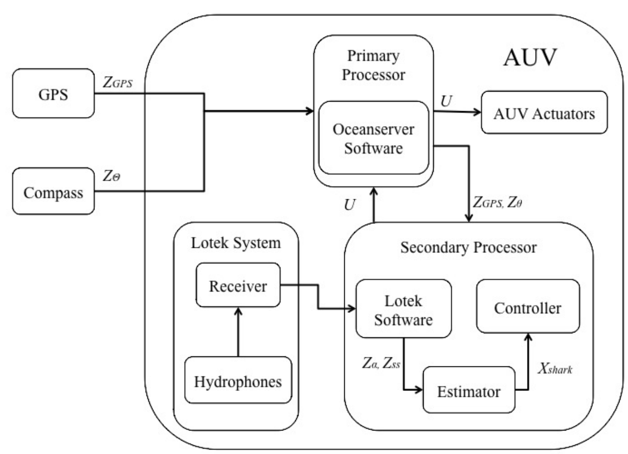


Fig. 2: Flow of control variables through the AUV tracking system, from sensors to actuators.

III. PROBLEM DEFINITION

The problem addressed in this paper is as follows. Given an AUV with stereo-hydrophone and receiver, design an estimator that determines the position, orientation, and velocity of a tagged shark in real time. The AUV used in this project is an Oceanserver IVER2 AUV (Fig. 1a), a torpedo shaped robot actuated with two fins to control pitch, two rear fins to control yaw, and a rear propeller to provide locomotion. As shown in Fig. 2, U represents the control vector sent to each of these five motors. The AUV's antenna has a built-in GPS receiver providing longitude and latitude measurements at a rate of 1 Hz. These position measurements are represented here as Z_{GPS}. The IVER2 also has a 3 degree of freedom compass. In this work the compass' yaw measurement Z_θ is required for shark state estimation.

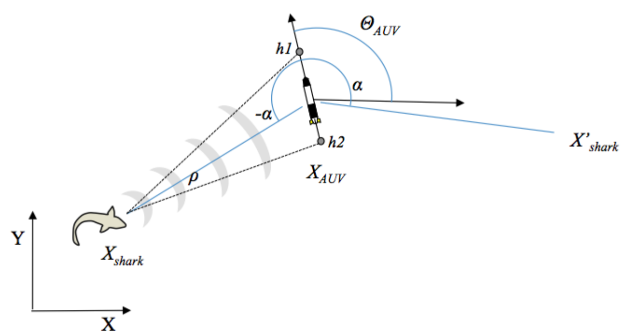


Fig. 3: Top Down View of Sample Measurement

The IVER2 has two processors, the primary which runs waypoint tracking missions, monitors the status of the robot's actuators, and enables sensor and actuator communications. The secondary processor is designated for external programs, and is where the acoustic receiver software, estimator, and controller are run. The receiver software produces measurements of the bearing to the tag Z_α and signal strength Z_{ss}, and passes these measurements to the estimator. The estimator processes the inputs, and outputs X_{shark} which it sends to the controller. The controller takes X_{shark} as an input, and uses this to make decisions about movement of the AUV relative to the estimated shark position.

The stereo-hydrophones, acoustic receiver, and receiver software are part of the Lotek MAP RT-A Hydrophone sensor system. The hydrophone system is designed to listen for frequencies of 76 kHz, the same frequency of signals emitted by the Lotek tags. The tags transmit encoded analog signals that allow them to be identified uniquely on the same frequency. An external frame was created in order to hold the stereo-hydrophones in place. The Lotek MAP RT-A system was designed to have the hydrophones set 2.4 meters apart, and at least one meter below the surface of the water. The hydrophone cables are internally connected and fed through sealed holes in the tail end of the hull of the AUV.

The estimation problem is depicted in Figure 3. In this figure a top down view of this system is shown with hydrophones h_1 and h_2 positioned just ahead of the AUV nose and just behind the AUV tail, respectively. X_{auv} represents the position and yaw of the AUV with respect to an inertial coordinate frame and determined by OceanServer's proprietary software. The estimator uses X_{auv} and Z_α as inputs to estimate the shark position and velocity X_{shark} at each time step t. More precisely, for $t \in [0, t_{max}]$:

Given:

$$X_{auv,t} = [x_{auv}\ y_{auv}\ \theta_{auv}\ \dot{x}_{auv}\ \dot{y}_{auv}\ \dot{\theta}_{auv}]_t \tag{1}$$

$$Z_t = [Z_{ss}\ Z_\alpha]_t \tag{2}$$

Determine:

$$X_{shark,t} = [x_{shark}\ y_{shark}\ \theta_{shark}\ v_{shark}\ w_{shark}]_t \tag{3}$$

Challenges associated with the stereo-hydrophone system include its limited range ($L = 100$ m), its low resolution ($= \pi/9$ rad), and the ambiguity of sign of the bearing angle. This ambiguity is illustrated in Figure 3, where the AUV cannot determine if a single bearing measurement Z_α corresponds to angle $+\alpha$ or $-\alpha$. X'_{shark} represents the other possible location of state based on the ambiguous sensor reading.

IV. STATE ESTIMATOR

A Particle Filter (PF) was used to estimate the state of the shark, with states defined in equation 3. The PF uses a collection of P particles to represent a probabilistic distribution of potential shark states. Each particle represents a single estimate of the shark state, with a position, orientation, velocity, and weight. Initially, each particle is randomly assigned a position, orientation, and velocity, by selecting from a uniform random distribution. Positions (x, y) are randomly selected from an L meter by L meter square area with the initial location of the AUV as the center of the distribution. Here, L reflects the range of the acoustic receiver system.

After being initialized, particles are updated with the PF algorithm that is called at each iteration of the AUV's control loop. The algorithm has two main steps, a $prediction$ step and a $correction$ step. The prediction step predicts the shark state of every particle. If a new valid signal from the shark tag is received, the likelihood or weight of all particles is calculated and the correction step will be called to resample the particle distribution. At the end of these two steps, the shark state estimate is calculated as the average position, orientation and velocity of all P particles.

A. Prediction Step

At every time step, each of the P particles in the set $\{X^p\}$ is propagated forward according to a first-order motion model. The motion model is a function of the previous particle position $(x^p_{shark}, y^p_{shark})$, orientation θ^p_{shark}, velocity v^p_{shark} and the uncertainty associated with these values, specifically the standard deviations σ_θ and σ_v. Steps 3 – 8 in Algorithm 1 show details.

Randomness is added to each propagated state by sampling from a Gaussian distribution with zero mean and standard deviations σ_θ and σ_v (i.e. with the function randn() in Algorithm 1). To note, velocity is additionally filtered within each particle using a weighted average of current estimate with the previous estimate. A weighting value of γ_{vt} is used to determine the dependency on new versus previous estimates within the average.

Algorithm 1 PF_Shark_State_Estimator($\{X^p\}$, X_{auv}, Z_α)

1: $//Prediction$
2: **for all** p particles **do**
3: $\quad v^p_{rand} \leftarrow v^p + randn(0, \sigma_v)$
4: $\quad \theta^p_{rand} \leftarrow \theta^p + randn(0, \sigma_\theta)$
5: $\quad x^p_{shark} \leftarrow x^p_{shark} + v^p_{rand} * \cos(\theta^p_{rand}) * \Delta t$
6: $\quad y^p_{shark} \leftarrow y^p_{shark} + v^p_{rand} * \sin(\theta^p_{rand}) * \Delta t$
7: $\quad v^p \leftarrow \gamma_{vt} * v^p + (1 - \gamma_{vt}) * \frac{\sqrt{(y^p_{shark} - y^p_{prev})^2 + (x^p_{shark} - x^p_{prev})^2}}{\Delta t}$
8: $\quad \theta^p \leftarrow \theta^p_{rand}$
9: $\quad$ **if** α is valid **then**
10: $\quad\quad \alpha^p_{exp} \leftarrow \text{atan2}(y_{auv} - y^p_{shark}, x_{auv} - x^p_{shark}) - \theta_{auv}$
11: $\quad\quad \alpha^p_{exp} \leftarrow g(\alpha^p_{exp})$
12: $\quad\quad w^p \leftarrow h(Z_\alpha, \alpha^p_{exp})$
13: $\quad$ **end if**
14: **end for**
15:
16: $//Correction$
17: **if** α is valid **then**
18: $\quad \{X^p\}_{temp} \leftarrow \{X^p\}$ for all p
19: $\quad$ **for all** p particles **do**
20: $\quad\quad X^p \leftarrow RandParticle(\{X^p\}_{temp})$
21: $\quad$ **end for**
22: **end if**

B. Correction Step

The correction is only run when a "valid" Lotek value is received. The expected bearing angle from the AUV to the particle's shark position, α^p_{exp} is calculated on line 10, and is adjusted for the rotation of the AUV, θ_{auv}, (see Figure 3). On line 12, the angle α^p_{est} is then converted from units of radians to Lotek angle units with the following function:

$$g(\alpha^p_{exp}) = -1 * 10^{-6}(\alpha^p_{exp})^3 + 2 * 10^{-5}(\alpha^p_{exp})^2 + 0.0947\alpha^p_{exp} - 0.2757 \tag{4}$$

The above function was defined through experimental testing of the Lotek system, and was generated from a Least Squares best fit line to those data plots. The angle, α^p_{exp}, is then rounded to the nearest whole number, since all Lotek angle values are integers between -8 and 8. The particle is then assigned a weight on line 13, through the following Gaussian weighting function:

$$h(\alpha, \alpha^p_{exp}) = 0.001 + \frac{1}{\sqrt{2\pi\alpha^p_{exp}}} * e^{\frac{-(|alpha^p_{exp} - Z_\alpha)^2}{2*\sigma^2_\alpha}} \tag{5}$$

The weight has a minimum value of 0.001, and is given a higher value when the particle's expected angle, α^p_{exp}, is closer to the measured angle, Z_α. As the angle difference decreases, a higher weighting is assigned.

The re-sampling is shown in Algorithm 1, lines 18 – 21. A copy of the propagated particle set is saved in $\{X^p\}_{temp}$. Then, each particle state is repopulated by randomly selecting from $\{X^p\}_{temp}$ using the function $RandParticle()$. This function selects a particle at random, with a likelihood of selection proporational to the particle's normalized weight. To improve the robustness of the algorithm, a small % of particles returned by this function will be newly generated random states.

TABLE I: Filter Parameter Values

Parameter	Value
σ_{auv}	5.0 meters
σ_v	0.3 meters per second
σ_θ	$\pi/2$ radians
σ_α	1.0 lotek angle units
σ_{ss}	15 lotek signal strength units
γ_{vt}	0.75

C. Sensor Modeling

There is a certain amount of error associated with every motion model propagation and sensor measurement. These errors are modeled as random variables that follow a zero mean Gaussian probability density function. The standard deviations associated with these functions, were derived both with experimental and historical data. The σ values in Table I represent the standard deviations used within this work.

V. EXPERIMENT DESCRIPTION

A. Avila Beach Pier Experiments

A series of validation experiments were performed at the Cal Poly Center for Coastal Marine Science (CCMS). The facility is located at the end of a large pier in Avila Beach, CA. These experiments included sensor characterization (e.g. determine σ_α), AUV tracking of a stationary tag, and AUV tracking of a moving tag.

During stationary and moving tag experiments, the AUV's start position relative to the tag was varied to ensure tracking could be performed from every direction. AUV start positions also were varied according to initial distance to the tag (i.e. 20, 50, 75, and 100 meters). For moving tag experiments, the tag was attached to either a human operated kayak or a second Iver2 AUV. During these experiments, the tag was fixed 2.0 meters below the surface, and the water depth was 10.0 meters. GPS measurements were recorded at the surface just above the tag's location.

Once the AUV was deployed for these experiments, it would autonomously track the tag's position estimates produced by the PF. To note, a controller was implemented

TABLE II: Mission Data

Mission Name	Date	Time	Mission Length min	Avg Error meters	Min Error meters	Max Error meters	Min Std Dev X meters	Max Std Dev X meters	Min Std Dev Y meters	Max Std Dev Y meters	Area Covered meters
sharkTrackA	8/9/11	10:41 AM	48.16	n/a	n/a	n/a	4.23	51.59	3.44	56.12	164.29 x 85.32
sharkTrackB	8/9/11	12:07 PM	37.25	n/a	n/a	n/a	4.95	52.10	2.79	46.89	62.85 x 50.10
sharkTrackC	8/9/11	2:42 PM	41.27	n/a	n/a	n/a	1.54	79.83	2.77	65.75	120.14 x 81.34
sharkTrackD	8/9/11	3:33 PM	1:41.27	n/a	n/a	n/a	1.91	80.91	2.34	87.72	103.62 x 69.69
auv2Track	8/10/11	11:19 AM	1:38.28	41.73	0.85	140.43	0.85	106.95	1.51	112.75	386.23 x 718.20
stationaryTrackA	8/7/11	4:19 PM	4.27	7.01	0.25	15.46	2.61	13.43	3.17	12.00	55.56 x 43.26
stationaryTrackB	8/7/11	4:24 PM	10.38	16.88	1.53	47.26	6.92	23.51	4.42	32.68	53.74 x 33.28
stationaryTrackC	8/7/11	4:47 PM	10.26	21.70	3.13	47.54	4.21	29.10	3.49	31.05	43.55 x 54.35

that would achieve two goals: *Minimize the distance between the AUV and tag* and *Minimize the time in which particles converge to the correct position of the tag*.

Given the direction to the tag is $\gamma_t = \alpha_t + \theta_{AUV,t}$, the controller directed the AUV to maintain its maximum propeller speed, while repeating on the following 3 steps: 1) track a desired heading of $\theta_{des} = \gamma_t + \pi/4$, then 2) track a desired heading of $\theta_{des} = \gamma_t - \pi/4$, and finally 3) track a desired heading of $\theta_{des} = \gamma_t$. This resulted in the AUV zig-zagging its way towards the AUV with 90 degree turns that help resolve the ambiguity in the sign of the bearing angle. For stationary tag experiments, the AUV terminated its mission when it was within 10 meters of the tag.

B. Port of LA Experiments

The experiments from CCMS were repeated in SeaPlane Lagoon, Los Angeles, CA, to verify accuracy and functionality at a new location. In addition to these same experiments, a leopard shark (*Triakis semifasciata*) was caught, externally fitted with an acoustic transmitter, and tracked. In some parts of the lagoon, eel grass became a problem both for AUV navigation and attenuation of the acoustic signal.

To catch a leopard shark for final validation of the system, a 10 hook long line was set in the lagoon and continuously monitored. Althogh several species of sharks were caught and released, a 1-meter leopard shark was externally dart tagged with an acoustic transmitter (Lotek MM Series, 76 kHz freq, 2,5 second ping rate), which is in standard use for tagging large marine fishes. The entire procedure took less than 10 minutes. Once the tagged shark was released, the AUV was deployed to track and follow the shark.

VI. RESULTS

For stationary tag tracking experiments, the error is defined as the distance between actual and estimated tag position. Fig. 4 shows the error during a typical experiment, which remains less than 18 meters during the experiment, and is on average less than 10 meters. Signal rate, i.e. the frequency of usable measurements, is also plotted. As expected, as signal rate decreases, standard deviations and error increase.

To demonstrate system performance with a moving target, results are presented from an experiment where an acoustic tag was attached to a second Iver2 AUV. Fig. 5(a) shows the paths for both the tracking vehicle (named AUV) and the tagged vehicle (named AUV2). AUV2 was manually driven within the lagoon, mimicking the relatively slow movement of a leopard shark. AUV autonomously tracked and followed AUV2 using the PF and controller described

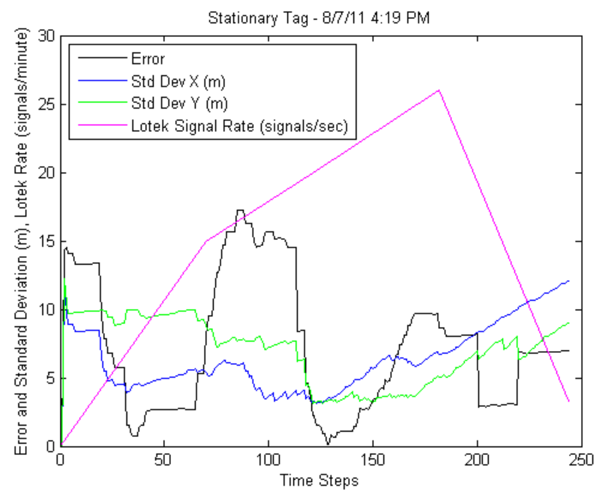
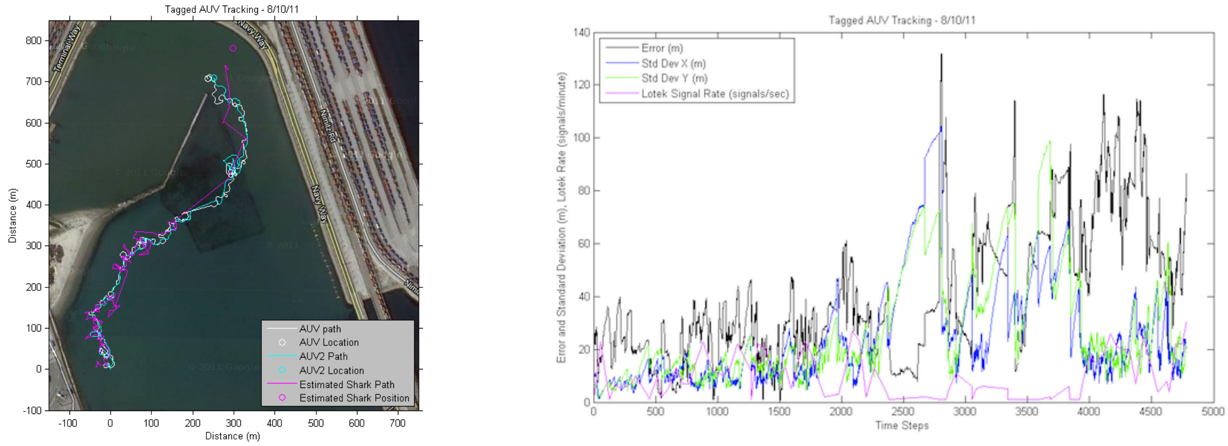


Fig. 4: Error, Standard Deviation, and Lotek Signal Rate from Tracking a Stationary Tag

above. The error, standard deviations, and signal rate can be seen in Figure 5(b). At t=2500 seconds, there is a significant increase in error. This corresponds with poor quality acoustic measurements we observed as the AUVs crossed an area with a high density of eel grass. This can be observed as this darker coloring in Fig. 5(a). Eel grass creates a curtain that dampens signal transmission.

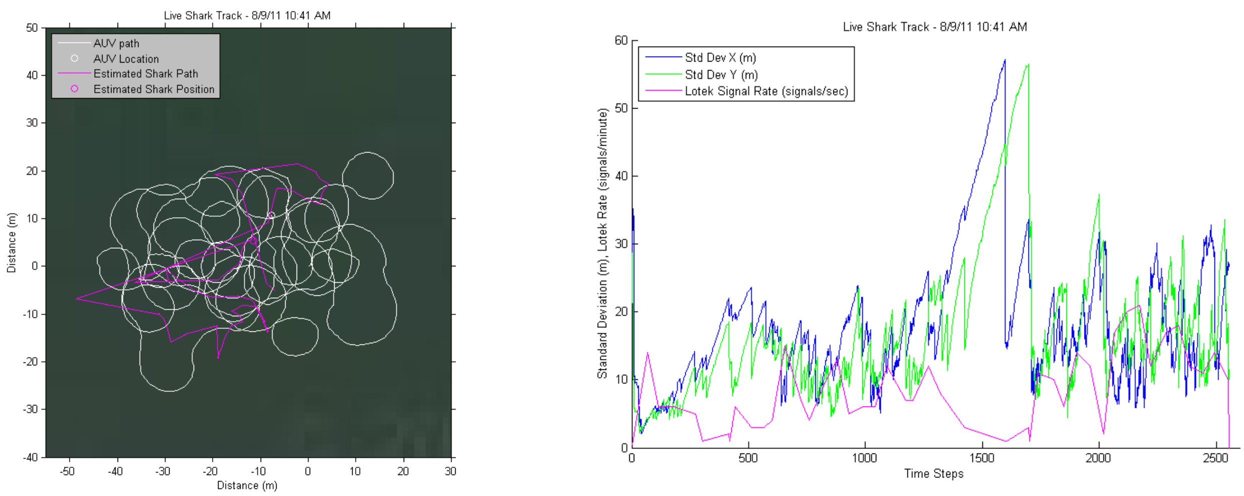
On August 9, 2011 a tagged leopard shark was tracked by the AUV for several hours with little interruption. The AUV and estimated shark paths from a 48-minute long tracking experiment are shown in Fig. 6(a). Fig. 6(b) shows the corresponding standard deviations of the particle set as well as the signal rate from the acoustic tag. While no estimation accuracy was obtained, these experiments demonstrated the ability for long term autonomous AUV tracking and following of a live shark. Table II summarizes the results, with a notable maximum tracking time of 1.67 hrs.

In Figure 7, a series of images represent the convergence of particles while tracking the tagged shark. In 7(a), the initial time step, the particles are randomly distributed throughout an L meter by L meter square area centered around the initial location of the AUV. The second image, 7(b), shows the beginning of particle convergence after a single acoustic signal is picked up by the hydrophones. The ambiguity in the sign of α can be observed here by the fact that particles are into two symetrical groups, one on



(a) (b)

Fig. 5: Tracking a tagged AUV: In (a), the trajectories of the tracking AUV, the tagged AUV2, and the estimated AUV2 are shown. In (b), the error, standard deviation, and Lotek signal rate of the same experiment are shown.



(a) (b)

Fig. 6: Tracking a tagged shark: In (a), the trajectories of the tracking AUV, the tagged shark, and the estimated shark are shown. In (b), the standard deviation, and Lotek signal rate of the same experiment are shown.

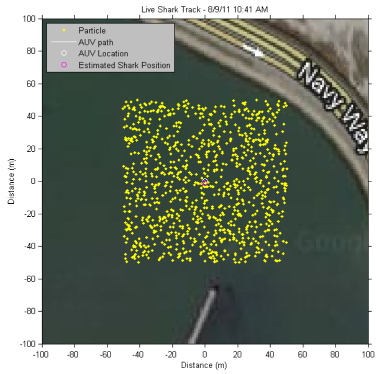
each side of the AUV. The third image, 7(c), depicts an instance when the AUV has rotated enough so that only one of the rays cast by the current bearing measurement (+Z_α or -Z_α) overlap with one of the existing particle groups. This geometric overlap leads to appropriate weighting of particles and convergence to a single accurate location. After a few more signals from the tag, and only 32 seconds after the initialization, the particles have consolidated into a tight distribution in 7(d).

These four images demonstrate the convergence that occurred during each experiment. The particles continually spread out through propagation, then were weighted and re-sampled after a Lotek measurement was obtained. It was a repeated cycle of expansion and contraction, with frequent contractions during a higher Lotek signal rate.

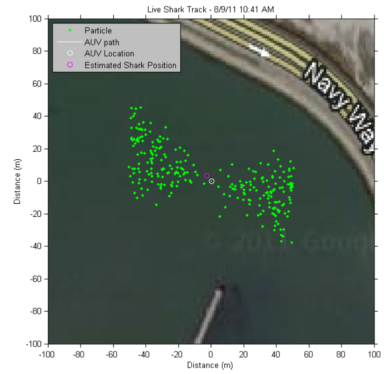
VII. CONCLUSIONS & FUTURE WORK

A state estimation method has been developed to enable tracking and following of a tagged sharks. The state estimator uses a Particle Filtering algorithm containing propagation and correction steps which control the movement of the particles. This filtering algorithm has been proven accurate through testing by localizing a stationary tag, tracking a tagged AUV, and a tagged shark. While tracking a second tagged AUV, the average error during the tracking was 41.73 meters, with a minimum value of 0.85 meters. A shark was continually tracked for a period of 1 hour and 41 minutes, thus validating this real system.

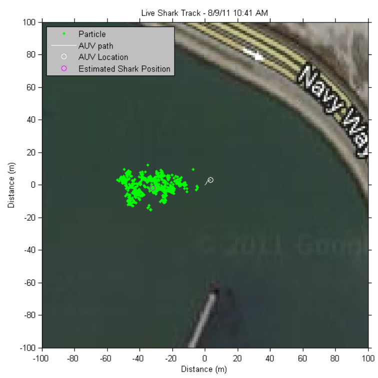
In the future, the tag signal strength may be calibrated with both an external sensor system as well as with the Lotek system in place. This could provide valuable range



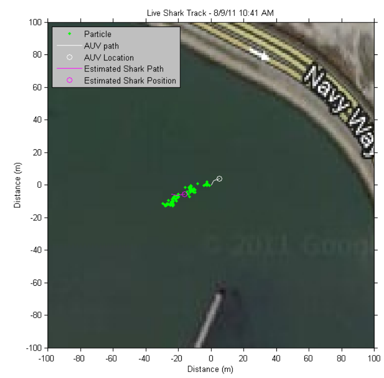
(a) t = 0.0 s



(b) t = 2.54 s



(c) t = 13.92 s



(d) t = 32.37 s

Fig. 7: Time Series of Particle Convergence

measurement, which may be required in tracking faster swimming sharks. Also, investigations into acoustic systems with greater range and more hydrodynamic hydrophone design will be conducted. Streamlining and reduction of the hydrophone profile will improve battery life of the AUV, reduce the likelihood of animal disturbance, and make the AUV more manuverable. Finally, this work promotes the use of collaborative multi-AUV tracking that may improve accuracy and reduce the likelihood of losing the shark.

References

[1] D. Fox, W. Burgard, F. Dellaert, and S. Thrun. Monte carlo localization: Efficient position estimation for mobile robots. In *Proceedings of the National Conference on Artificial Intelligence*, pages 343–349. JOHN WILEY & SONS LTD, 1999.

[2] C. Georgiades, A. German, A. Hogue, H. Liu, C. Prahacs, A. Ripsman, R. Sim, L.A. Torres, P. Zhang, M. Buehler, et al. Aqua: an aquatic walking robot. In *Intelligent Robots and Systems, 2004.(IROS 2004). Proceedings. 2004 IEEE/RSJ International Conference on*, volume 4, pages 3525–3531. IEEE, 2004.

[3] Thomas M. Grothues. A review of acoustic telemetry technology and a perspective on its diversification relative to coastal tracking arrays. *Tagging and Tracking of Marine Animals with Electronic Devices*, Diversification of Acoustic Telemetry Technology:77–90, 2009.

[4] T.M. Grothues, J. Dobarro, J. Ladd, A. Higgs, G. Niezgoda, and D. Miller. Use of a multi-sensored AUV to telemeter tagged atlantic sturgeon and map their spawning habitat in the hudson river, USA. In *Autonomous Underwater Vehicles, 2008. AUV 2008. IEEE/OES*, pages 1–7. IEEE, 2008.

[5] T.M. Grothues and J.A. Dobarro. Fish telemetry and positioning from an autonomous underwater vehicle (AUV). *Instrumentation ViewPoint*, (8):78, 2009.

[6] J. Rife and S. M. Rock. Segmentation Methods for Visual Tracking of Deep-Ocean Jellyfish using a Conventional Camera. *IEEE Journal of Oceanic Engineering*, 28(4):595–608, 2003.

[7] D. Schulz, W. Burgard, D. Fox, and A.B. Cremers. Tracking multiple moving targets with a mobile robot using particle filters and statistical data association. In *Robotics and Automation, 2001. Proceedings 2001 ICRA. IEEE International Conference on*, volume 2, pages 1665–1670. IEEE, 2001.

[8] D. Schulz, W. Burgard, D. Fox, and A.B. Cremers. People tracking with mobile robots using sample-based joint probabilistic data association filters. *The International Journal of Robotics Research*, 22(2):99, 2003.

[9] D.W. Sims, E.J. Southall, A.J. Richardson, P.C. Reid, and J.D. Metcalfe. Seasonal movements and behaviour of basking sharks from archival tagging: no evidence of winter hibernation. *Marine Ecology Progress Series*, 248:187–196, 2003.

[10] S. Thrun, D. Fox, W. Burgard, and F. Dellaert. Robust monte carlo localization for mobile robots. *Artificial Intelligence*, 128(1-2):99–141, 2001.

[11] Sebastian Thrun, Wolfram Burgard, and Dieter Fox. Probabilistic robotics. In *Probabilistic Robotics (Intelligent Robotics and Autonomous Agents)*, USA, sept. 2005. The MIT Press.

[12] A. Treptow and A. Zell. Real-time object tracking for soccer-robots without color information. *Robotics and Autonomous Systems*, 48(1):41–48, 2004.

[13] F.A. Voegeli, M.J. Smale, D.M. Webber, Y. Andrade, and R.K. O'Dor. Ultrasonic telemetry, tracking and automated monitoring technology for sharks. *Environmental Biology of Fishes*, 60(1):267–282, 2001.

[14] Jun Zhou and Christopher M. Clark. Autonomous fish tracking by rov using monocular camera. *Computer and Robot Vision, Canadian Conference*, 0:68, 2006.