Behavior Characterization and Particle Filter Localization of a Shovelnose Shark

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Abstract—Acoustic tags allow researchers to track sharks and other fish with a relatively high degree of accuracy in either 2 or 3 dimensions. The tags transmit a sound wave from the shark or fish to any receiving hydrophone within range. By using 2 or 3 receivers, in known locations, the geo-referenced location of a tagged shark can be calculated.

This project focuses on the problem of improving localization of a shark, by filtering the position measurements received from an acoustic tag system.

First, a 24 hour data log of position measurements of a shovel nose shark was used to characterize shark motion behaviors. Using a new clustering algorithm, the data log was broken into groups of which have similar velocity magnitudes. Each group was characterized as a behavior with a velocity mean and standard deviation.

Second, a new shark state estimator was designed based on a two step iterative process that is triggered every time a new measurement is obtained. In step 1, the current position measurement is used to calculate the likelihood that the shark is in each of the behaviors. In step 2, the most likely of the behaviors is used as a first order motion model to predict where the shark is going between measurements. Specifically, this model is used in a Particle Filter (PF) to propagate particles (each representing an individual estimate of the shark state) forward in time. Each particle is assigned a likelihood that it represents the actual shark state based on how close the particle's position matches the recent position measurement. The PF then resamples the particles, effectively removing particles of lower likelihoods and reproducing particles of higher likelihoods.

Offline processing of the real shark data shows that the localization and prediction of the shark's future location are improved when compared with differentiating location measurements. In the future, this state estimation strategy will be used on board an Autonomous Underwater Vehicle (AUV), enabling the AUV to track sharks in real time.

I. INTRODUCTION

Underwater tracking technologies exist in many forms, all with their pros and cons. Acoustic tags send out a coded signal via sound waves that uniquely identify each tag and only when a receiver is within range is that data recorded [1]. Satellite tags can only transmit their data if a tagged animal nears the surface of the water and are much more flexible [2]. Pairing an acoustic tag with a boat following the tagged animal gives some flexibility for acoustic tags but requires at least one human operator. This paper considers the potential to use an Autonomous Underwater Vehicle (AUV) to track the acoustically tagged animal. One type of animal that's particularly difficult to track are sharks. They commonly have long migratory paths that would make a satellite tag much more appealing than an acoustic tag for tracking purposes. However, using an AUV to track an acoustically tagged shark allows for obtaining shark states while underwater, as opposed to just being able to obtain surface measurements.

One of the main problems in using AUVs to track a shark consists of localizing the shark. The AUV needs to know where the shark is in relation to it so that it can make the correct decisions as to where to go. If historical data about the shark is available, the AUV's algorithm can be improved greatly. By filtering the measurements using historical data, the AUV can make better predictions as to where the shark will go. Unfiltered measurements can be used to track the shark but will produce less accurate predictions. This paper presents an algorithm for localizing an acoustically tagged shark using past behavior as a guide.

II. BACKGROUND

Acoustic tagging systems in general include two parts: a transmitter and a receiver. The transmitters (a.k.a. "tags") can be implanted into or attached to aquatic life and transmit an acoustic signal. That signal is encoded in specific ways to make each tag uniquely identifiable, thereby making it possible to track specific animals with a set of receivers. More sophisticated tags can also transmit sensor information via their acoustic signal that would then have to be decoded by the receiver. The receivers, usually one or more hydrophones,
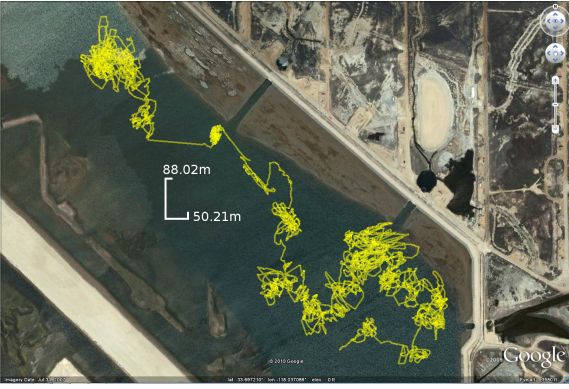
Fig. 1: Shovelnose Shark trajectory over 24 hours

(a) t1 and t2 (b) t3 and t4

Fig. 2: Closeup of Trajectory at interesting time-steps

contain most of the power of the system. The receivers are responsible for decoding the tag's signal and when more than one receiver is used in known locations the location of the transmitting tag can be calculated using the travel time of the signal from the tag. This calculation can either be done on attached electronics or the data can be sent (via cables or radio waves) to a base station to do the calculations.

In the past acoustic tags have been mostly paired with fixed receivers or with hydrophones mounted to or towed by crewed boats. In some cases where fixed arrays of hydrophones use compatible technology tagged fish can be tracked in more than one location, in one case Maine and Virginia [1]. The desired resolution in time and space of the data set greatly affects the type of acoustic system deployed.

III. DATA SET

The data set used in this work was obtained by Dr. Chris Lowe in 2008 using a VemCo tagging system installed at Bolsa Chica Ecological Reserve in Southern California. It consists of latitude and longitude data from one Shovelnose shark, and can be seen in Fig. 1. The shark was tagged with an acoustic transmitter that was then used in conjunction with static receivers to triangulate the shark's positions. Each latitude and longitude measurement pair was time-stamped to the second. A close up view of two areas of interest is shown in Fig. 2. In Fig. 2, (a) and (b), t2 and t4 are both 1000 time-steps away from t1 and t3 respectively; where each GPS measurement received is one time-step. Before being filtered to improve shark state estimation, the latitude-longitude coordinates were translated into an x-y coordinate system with the origin located at the latitude (x) and longitude (y) of the first data point. This was accomplished using Vincenty's algorithm to calculate the distance between each data point and the first data point [3]. The result was a set of m measurements termed Z.

$$Z = \{z_l = [t_l x_l y_l]\, | \, l = 1..m\} \tag{1}$$

IV. SHARK STATE ESTIMATION

To estimate the location of the shark a Bayes Filter and a Particle Filter were used in a multi step process. The Bayes
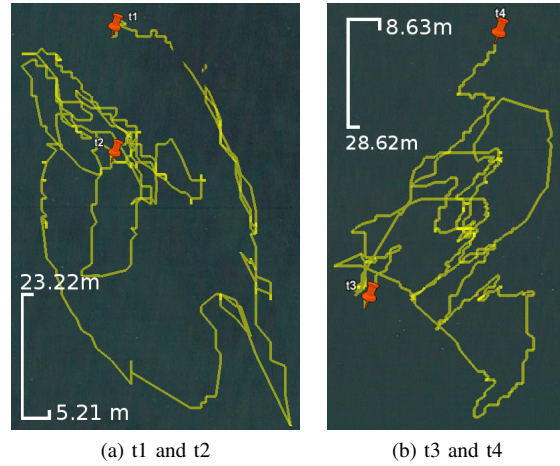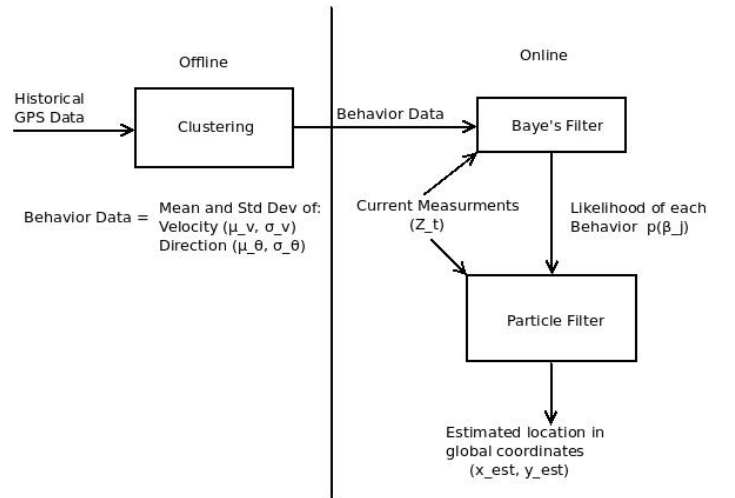

Fig. 3: Block diagram of algorithm

Filter, described in Section IV-B, estimates the shark's current behavior. The Particle Filter, described in Section IV-C, uses the mean velocity and mean direction associated with each behavior to track the likely position of the shark. The data set is first clustered to calculate n standard shark behaviors. A Bayes Filter is used because it estimates the likelihood of a finite set of discrete states which maps well to the set of n behaviors.

A. Behavior Characterization

To develop some behaviors useful for characterizing motion, the measurements in Z were used to calculate the shark's velocity magnitude, and orientation associated with each time step. These values were calculated using an average of the previous 30 minutes of data. This data was then input into the clustering algorithm.

The first round of clustering begins by evenly dividing the measurements from Z into o clusters. In this case, a cluster C_i is defined by two bounding time indexes d_i and d_{i+1}.

$$C_i = \{z_l | d_i \leq l \leq d_{i+1}\} \tag{2}$$

The clustering algorithm iterates m times over the following steps:

1) Calculate the mean ($velMean_i$) and standard deviation ($velSTD_i$) of the velocity for each cluster i.
2) For each cluster i:

$$d_i = \begin{cases} d_i - rand(\theta, \Upsilon) \text{ if } \gamma_{-,i} > \gamma_{+,i} \\ d_i + rand(\theta, \Upsilon) \text{ else} \end{cases} \tag{3}$$

$$\forall i = 1...o$$
$$\gamma_{-,i} = |velocity(d_i) - velMean_i|$$
$$\gamma_{+,i} = |velocity(d_i) - velMean_{i+1}|$$

The n final clusters are then selected that characterize the velocity distribution. These n clusters are made of multiple clusters from the first round of clustering. The mean and standard deviation of the velocity and orientation of these final n clusters are calculated and become the parameters that characterize each behavior.

B. Shark Behavior Estimation

A Bayes' Filter is used at each time step to estimate of the probability the shark is in each behavior β_j.

1) Propagation: Once the probability of a behavior passes a predetermined threshold γ, it is recognized as the most likely behavior for a predetermined amount of time. The last time-step that each behavior passed γ is also stored as u_j. The predetermined amount of time c used in this algorithm was two times the average amount of time spent in a behavior (determined using the clustering algorithm). These time-steps are used in the propagation step of the Bayes Filter. At each time step the Bayes Filter will calculate the time difference between the current time-step and u_j. It will then predict the probability of each behavior $p(\beta_j)$ by summing over the probabilities of transitioning from each behavior at the last time-step.

$$p'(\beta_{i,t+1}) = \sum p(\beta_{i,t+1}|\beta_{j,t}) * p(\beta_{j,t}) \tag{4}$$

The first term, $p(\beta_{i,t+1}|\beta_{j,t})$, is calculated in three ways depending on the probability of the ith behavior and whether or not j equals i.

Caseone : If the probability of the ith behavior is greater than the predetermined threshold and j equals i, then the first term equals one minus the value returned from a sigmoid function of the difference in time calculated earlier, the average time spent in a behavior and the variance in time spent in a

behavior. This sigmoid function is calculated as follows:

$$f(t, u_j, \sigma_t) = \frac{1}{1 + e^{-\alpha * t}} \tag{5}$$
$$\alpha = \frac{s - \mu}{\sigma_t^2}$$
$$s = t - u_j$$
$$\mu = \frac{24}{o} * 3600$$
$$\sigma_t^2 = 1800$$

Casetwo : If the probability of the ith behavior is greater than the predetermined threshold but j does not equal i, then the first term equals one divided by one less than the number of behaviors multiplied by the value calculated in the same manner as case one.

Casethree : if neither of the two cases apply, then the first term equals one divided by the number of behaviors. The preceding three cases are expressed as formulas below.

$$p(\beta_{i,t+1}|\beta_{j,t}) = \begin{cases} 1 - f(t, u_j, \sigma_t) \text{ if } i = j \text{ and } p(\beta_j) > \gamma \\ (\frac{1}{n-1})(1 - f(t, u_j, \sigma_t)) \text{ if } i \neq j \text{ and } p(\beta_j) > \gamma \\ \frac{1}{n} \text{ else} \end{cases} \tag{6}$$

2) Correction: Whenever a new measurement z_l becomes available, the Bayes Filter will perform a correction step to take into account the new measurement. The equation used for the correction step is shown in (7). A Gaussian probability density function is used to determine the probability that the current shark velocity would occur for each behavior. This probability is multiplied with the current probability of each behavior and then divided by the $p(Z_{t+1})$ term listed in (8). The $p'(\beta_{i,t+1})$ term is the probability calculated in the propagation step (see (4)).

$$p(\beta_{i,t+1}) = \frac{p(Z_{t+1}|\beta_{i,t+1}) * p'(\beta_{i,t+1})}{p(Z_{t+1})} \tag{7}$$

$$p(Z_{t+1}) = \sum_{i=1}^{n} p(Z_{t+1}|\beta_{i,t+1}) * p'(\beta_{i,t+1}) \tag{8}$$

In (8), the n term is the number of behaviors calculated by the algorithm outlined in Section IV-A. The $p(Z_{t+1}|\beta_{i,t+1})$ term is calculated by inputing the current velocity magnitude of the shark (as v) into a guassian function with a mean and standard deviation from the current behavior i's velocity magnitude mean $\bar{v}_i$ and standard deviation $\sigma_{v,i}$.

$$p(Z_{t+1}|\beta_{i,t+1}) = \frac{1}{\sqrt{2\pi\sigma_{v,i}}} * e^{\frac{-(v - \bar{v}_i)^2)}{\sigma^2}} \tag{9}$$

C. Particle Filter Localization

Particle Filters work by keeping many state estimates in memory, propagating those state estimates forward at every time-step, and correcting the state estimates when new sensor data is available. Each one of these many state estimates is named a particle that also includes a weight that represents the likelihood the particle's state is the actual state. The weights

determine which particles reproduce during the correction step and which die off. In this work each particle consists of an x, y, θ (orientation), and w (or weight). By averaging all p particles (or state estimates), a fairly accurate estimate of the actual state can be calculated.

1) Propagation: At every time step the Particle Filter uses the mean and standard deviation of velocity associated with the behavior of highest likelihood β_j to propagate particles. For each particle k, the algorithm calculates a new velocity $v_{k,t+1}$ using the old velocity of the particle as a base and adds a random change by sampling from a guassian distribution of $\sigma_{v,j}$. It also calculates a new orientation for each particle, by adding a random change in orientation by sampling from a guassian distribution of $\sigma_{\theta,j}$. Using the particle's old position x, y and the new velocity, direction and the change in time, a new x and y position are calculated for the particle.

$$\forall k = 1...p$$
$$j = min_{\beta_j}|v_j - v_t|$$
$$v_{k,t+1} = v_{k,t} + \sigma_{v,j} * randn()$$
$$\theta_{k,t+1} = \theta_{k,t} + \frac{\sigma_{\theta_j} * randn()}{5}$$
$$x_{k,t+1} = x_{k,t} + v_{k,t} * cos(\theta_{k,t}) * \delta_t$$
$$y_{k,t+1} = y_{k,t} + v_{k,t} * sin(\theta_{k,t}) * \delta_t$$

2) Correction: Whenever a new latitude-longitude measurement is received, each particle k is given a weight based on how close it's new position $[x_{k,t+1}, y_{k,t+1}]$ matches the measured position z_t of the shark.

$$dist_k = \sqrt{(x_z - x_k)^2 + (y_z - y_k)^2} \quad (10)$$
$$weight_k = \frac{1}{\sqrt{2\pi}\sigma_z} * e^{-(dist_k^2)/(\sigma_z^2)} \quad (11)$$

The Particle Filter then randomly selects a new set of particles from the old set, where old particles with higher weights are more likely to be chosen to be a part of the new set. The estimated position of the shark is the weighted average of all the particle's positions at each time-step. The algorithm then calculates an error in the estimated position of the shark against the actual measured position z_t using the absolute distance between the two points.

V. RESULTS

A. Behavior Characterization

For the Shovelnose data set clustering of the behaviors was accomplished using $o = 25$ behaviors, and $m = 300$ iterations. As can be seen in Fig. 4, the mean standard deviation in velocity for all the clusters falls off nicely and then stabilizes. This demonstrates that as the clustering algorithm iterates, measurements belonging to each cluster will share more similar velocity magnitudes. The final round of clustering chose a set of $n = 3$ behaviors.

Another way to check the performance of the clustering algorithm is to observe which velocity is associated with each cluster. A graph of these results can be seen in Fig. 5 and
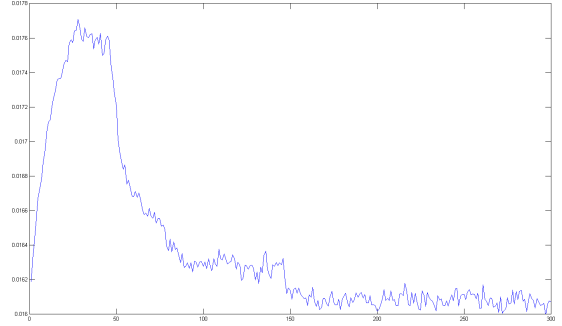

Fig. 4: Mean Standard Deviation of Clusters

TABLE I: Values of Parameters

Parameter	Value
o	25
m	300
n	3
γ	0.5
p	150

shows that the clusters do a good job of representing the different velocities.

B. Shark Behavior Estimation

To determine the correctness of the Bayes Filter, the behavior β_j whose velocity magnitude $\bar{v}_j$ most closely matches the current velocity v_t at each time-step was used as a reference. This is shown in Fig. 6. In the bottom graph of that figure, the values 1, 2 and 3 correspond to each of the 3 behaviors that the clustering algorithm output in order of lowest (behavior 1) to highest (behavior 3) mean velocity magnitude. Also at time-steps t1-t4 (where the shark's position is graphed at those time-steps in Fig. 2), it can be seen that the velocity magnitude of the closest behavior at those time-steps corresponds well with the distance covered during these time steps. Between t1 and t2 the shark had a low velocity and traveled a small distance whereas between t3 and t4 the shark had a large velocity and traveled a larger distance.

Using the closest behavior as a reference, the probability of each behavior at each time-step can be compared with the Bayes Filter behavior estimates. These probabilities are graphed in Fig. 7. The probability of behavior two and three are very low and the probability of behavior one is close to 100% at t1 and t2 in Fig. 7 just as the closest behavior in Fig.
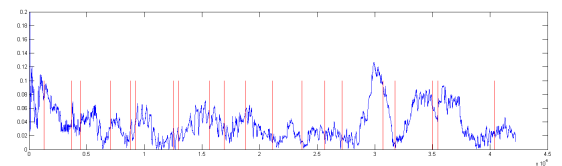

Fig. 5: Velocity Magnitude clustered into o=25 clusters, denoted by dividing lines.
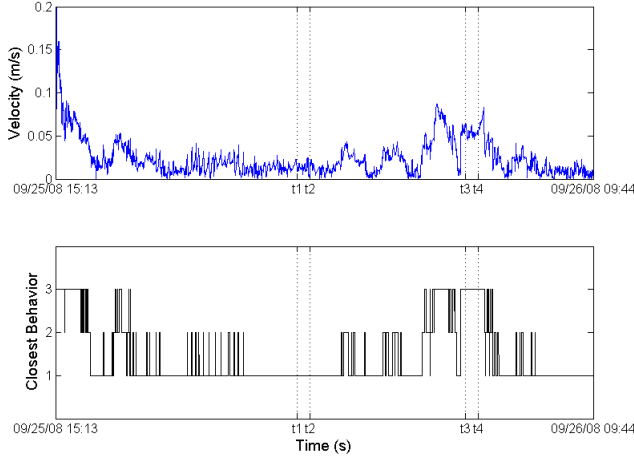
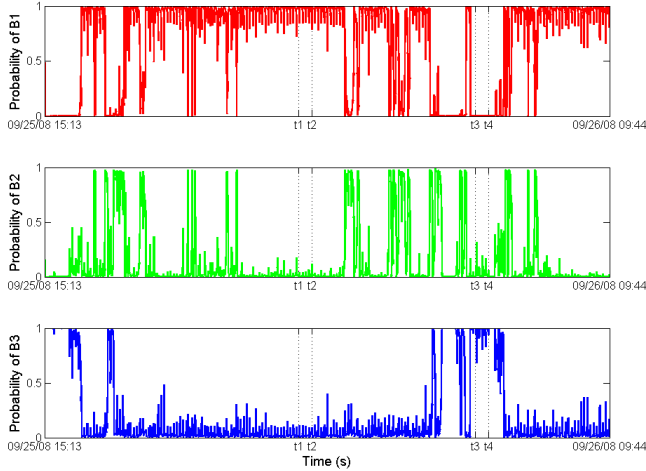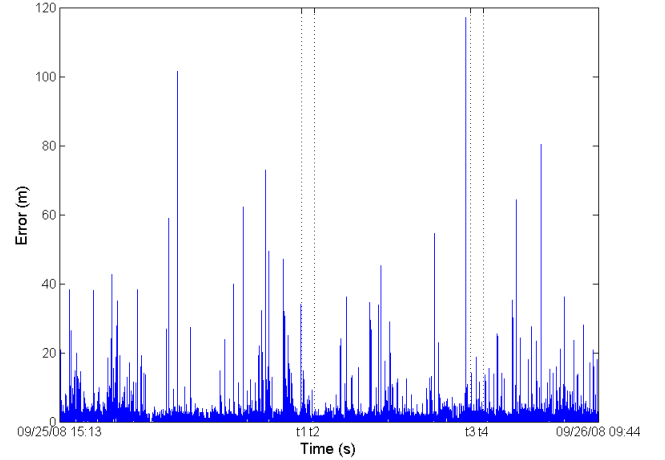Fig. 6: Velocity Magnitude and closest Behavior over time

Fig. 7: Probability of Each Behavior over time

(a) Simple Prediction

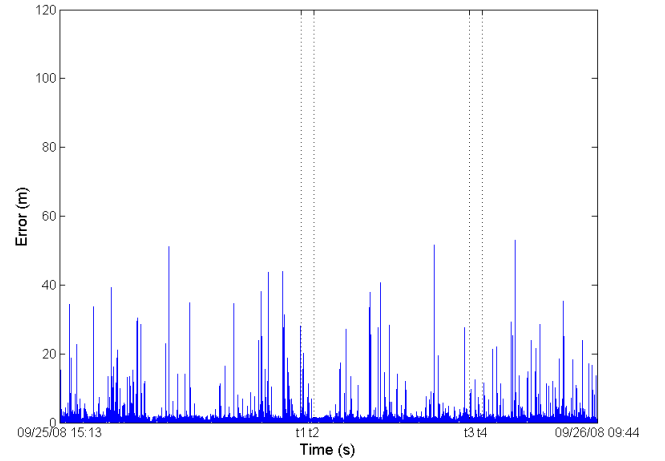(b) Localization Algorithm

Fig. 8: Error

6 is behavior 1 at both those time-steps. Also, at t3 and t4 the probability of behavior 3 is very high (and 1 and 2 are very low) just as the closest behavior is behavior 3.

C. Particle Filter Localization

To evaluate the particle filter's ability to predict future shark states, a predicted location was calculated using just the previous two measurements z_{t-1}, z_{t-2} for every time-step. The error between the state predicted and that measured z_t was used as a comparison to the localization algorithm detailed in Section IV-C, see (12) for the exact formula. Comparing the localization algorithm and the simple prediction is done via calculating the mean error across the entire run. The simple prediction resulted in a mean error of 1.34 meters whereas the localization algorithm resulted in a mean error of 1.00 meters when run across the entire data set. This is a reduction in the error of about 33%. A graph of the error using the simple prediction is provided in Fig. 8(a). A graph of the error using the localization algorithm is provided in Fig. 8(b). Table II shows a summary of the comparison between the localization algorithm and the simple prediction.

TABLE II: Mean and Max Error for the Simple Prediction (S.P.) and Localization Algorithm (L.A.)

	Mean Error	Max Error
S.P.	1.34 m	117.17 m
L.A.	1.00 m	54.02 m

$$error = \sqrt{(x_z - x_{est})^2 + (y_z - y_{est})^2} \qquad (12)$$
$$x_{est} = \frac{\sum_{k=1}^{p} w_k * x_k}{\sum_{k=1}^{p} w_k}$$
$$y_{est} = \frac{\sum_{k=1}^{p} w_k * y_k}{\sum_{k=1}^{p} w_k}$$

VI. Conclusion and Future Work

In this paper a localization algorithm for a Shovel-nose shark is presented. It was shown that using an algorithm that meshed a Bayes Filter and a Particle Filter can decrease the error in location predictions. The algorithm's error was compared to the error when the location was predicted using only the last two GPS coordinates. While the algorithm presented in this paper can give a prediction as to where a Shovel-nose shark is located, more work in necessary to generalize the algorithm to other sharks as well as take advantage of the algorithm within one or more Autonomous Underwater Vehicles (AUVs). This will be accomplished using more data sets.

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