Behavioral characterization and Particle Filter localization to improve temporal resolution and accuracy while tracking acoustically tagged fishes

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Abstract

Quantifying the fine-scale movement patterns and habitat use of active fishes has historically been challenging due to their scope of movement or the labor intensive nature of actively tracking potentially wide-ranging species. This project focuses on improving the localization accuracy and temporal resolution of an acoustically tagged fish by filtering the position measurements received from an acoustic receiver array. Using the $k$-means clustering algorithm, data sets are broken into groups which have similar fish speeds and yaw rates to yield a discrete number of movement behaviors characterized by the mean and standard deviation of speed and yaw. Next, a Particle Filter state estimator is proposed, in which position and speed state estimates of particles are used to calculate the most likely motion behavior, which in turn is used as a first order motion model to propagate the particle’s fish state estimates forward in time. These predicted particle states are compared with the position measurements and then resampled as done with most Particle Filters. Offline processing of a shovel-nose guitarfish (Rhinobatos productus) data set shows that the estimation of the fish’s location is improved during periods of time when no measurements could be obtained when compared with two common filtering approaches.

Keywords: Fish tracking, Acoustic tagging, State estimation, Particle filtering, Bayesian filtering

1. Introduction

Understanding the movement patterns of aquatic animals through observation and modeling can provide us with essential information to make decisions that affect our environment, health, finances, and safety. Historically, the study of movement patterns has involved marking (tagging) individual fish within a population in order to characterize their movements relative to environmental conditions or social context. The ultimate goal of tracking individuals has been to identify patterns of movement across a population that would provide data needed for predictive modeling. High resolution tracking of individual fish within a population has always been challenging. While tracking technology itself has limited the rate and resolution at which new data can be acquired, recent advances in filtering, sensor fusion and modeling are enabling post-processing of measurements to produce more accurate and informative movement estimates.

Autonomous Underwater Vehicles (AUVs) that autonomously track and follow a tagged fish have the potential to overcome the current limitations on data acquisition. They are now capable of swimming complex transects while simultaneously collecting environmental data (Dickey et al., 2008). Vastly improved navigational and geospatial positioning abilities of AUVs now indicate that they could also be used to track large, highly mobile tagged fish while simultaneously collecting environmental data. The authors have made substantial progress along this front (Forney et al., 2012), and the need to enable and improve accurate real-time fish state estimation on board AUVs motivates this work.

Presented here is a method for modeling different behavioral states of fish from historical data sets obtained by tagging and tracking the individual with an acoustic tracking system, and using those behaviors to better predict and more accurately localize the fish’s position during time periods when no measurements are available. Section 2 provides a background on related tracking technology as it applies to coastal environments. The problem being solved in this work is defined in Section 3. A target data set is then described in Section 4 that is used to validate the behavior and position estimation algorithms. Next, a method for characterizing behaviors is presented in Section 5. The proposed state estimators designed for this work are described in Section 6.
which includes details of the Particle Filter design. This is followed by results in Section 7 and conclusions in Section 8.

2. Background

While a wide variety of underwater tracking technologies exist, the limitations of positional accuracy, spatial coverage, degree of labor intensity, and operational costs have limited movement studies of large, highly mobile fishes, such as sharks (Lowe and Goldman, 2001).

Fine-scale fish movements are typically quantified with an acoustic telemetry tracking system, generally composed of two parts: a transmitter and a receiver. The transmitters, often referred to as “tags”, can be implanted into or attached to a fish and are designed to emit an acoustic signal between 30 and 200 kHz, depending on the size of the animal and the environmental conditions. The transmitter can produce a uniquely identifiable ultrasonic pulse or pulse train, at fixed or varied intervals that enable the fish to be localized using an array of omni-directional underwater receivers or a mobile shipborne receiver and directional hydrophone (Espinoza et al., 2011; Grothues, 2009; Lowe and Bray, 2006). The distance from which a fish can be tracked is limited by the power output of the transmitter, but typically varies between 50–1000 m. More sophisticated tags can also transmit sensor information (e.g., depth, temperature, acceleration vectors) via their acoustic signal that would then have to be decoded by the receiver.

The receivers, and usually one or more hydrophones, contain most of the power of the system and are responsible for decoding the tag’s signal. Underwater receiver arrays allow for a fish’s position to be derived by trilateration of the transmitter emission using time of arrival of the transmitter pulse to neighboring receivers. This technique allows for quantification of environmental parameters in addition to movements of multiple fishes; however, if tagged fish exhibit scopes of movement larger than the array, individuals cannot be tracked and positional accuracy decreases as the fish near the perimeter of the array (Espinoza et al., 2011). For example, the migratory movements of fishes tagged in estuaries along the western Atlantic have been monitored using arrays in locations such as Maine and Virginia, and also between estuaries in the eastern Pacific (Grothues, 2009). The alternative approach is to actively follow a tagged fish from a vessel using a directional hydrophone and shipborne receiver to determine bearing and distance based on signal strength and direction. This method can be extremely labor intensive and cost prohibitive, especially for large, highly mobile species (Bertrand et al., 1999; Dagorn et al., 2000).

In response to the limitations on these tracking methods, i.e., static receiver arrays and tracking with a human driven surface vessel, efforts to implement receiver systems on Autonomous Underwater Vehicles (AUV) have been carried out. In Forney et al. (2012), a leopard shark was tagged, tracked and autonomous followed using a stereo hydrophone pair mounted on the AUV. Of note, the AUV ran a Particle Filter to estimate the shark position in real time.

Using offline processing of data sets obtained from tagging and tracking individual animals with static receiver arrays, mathematical models that attempt to describe the motion tendencies of the individuals have been developed and verified. At the population level, diffusion models have been applied to a variety of species (Hilborn, 1990; Johnson et al., 1992; Skalski and Gilliam, 2000).

At the individual level, diffusion modeling can be incorporated into an individual’s movements using a particle based approach that models motion as a random walk, e.g., Bailey and Thompson (2006). Several types of random walks have been considered including Brownian motion and Levy flights (Sims et al., 2011), as well as mixtures (Morales et al., 2004). For example, the Levy flight foraging hypothesis, that optimal foraging for predators is accomplished with Levy flights when prey is sparse, was confirmed for particular shark species for which extensive tracking data existed in Humphries et al. (2010). The uncertainty of such motion models was incorporated into a state space formulation in Jonsen et al. (2005), allowing comparison between different motion behavior models via error covariance.

Other particle models assume individuals follow simple kinematic equations that are affected by the state of its local neighbors (Hensor et al., 2005; Huse et al., 2002; Katz et al., 2011). For example, in Hensor et al. (2005), an individual’s motion is a function of its repulsion, alignment and attraction to other individuals. From these interactions, there can emerge general trends in the movement of the population. This is often seen in shoaling, schooling, and aggregating species (Hensor et al., 2005). This grouping behavior and the predictability of the movements of the group can have great consequences on dispersal of bio-accumulated contaminants, over-harvesting, and ultimately ecosystem health (Hensor et al., 2005).

Also related is the recent analysis of active tracking data by Papastamatiou et al. (2009), Papastamatiou and Lowe (in press) have found that different species of sharks exhibit different scales and patterns of movement depending on habitat and other behavioral motivations, such as foraging. Changes and amplitude of these patterns could be identified using fractal analysis.

With the goals of modeling fish movement behavior, increasing fish localization accuracy, and enable improved real time AUV tracking performance, this paper presents a new approach to filtering data with an algorithm that combines a Bayes Filter to first characterize the behavior of the fish being localized, with a Particle Filter localization algorithm.

3. Problem definition

The objective of this work is to develop an approach to filtering tracking data to: (1) determine behavioral patterns of the fish being tracked so they can later be correlated with environment parameters and (2) produce higher resolution positioning information of fish—especially during times when no acoustic measurements are or were available.

Specifically, let the data set \( Z \) represent \( m \) measurements composed of a time stamp \( z_{t,i} \), latitude \( z_{x,i} \), and longitude \( z_{y,i} \), with the \( i \)-th measurement defined as \( z_i \).

\[
Z = \{z_i = [z_{t,i}, z_{x,i}, z_{y,i}] | i = 1 \ldots m \} \tag{1}
\]

The filtering approach must construct the set \( P \), composed of \( n > m \) state estimates. Each state includes a time stamp \( p_{t,j} \), latitude \( p_{x,j} \), and longitude \( p_{y,j} \), with the \( j \)-th estimate termed \( p_j \). In this case, the time step size between estimates is \( \delta t = (z_{t,m} - z_{t,1})/n \) such that the time interval from \( z_{t,1} = z_{x,1} \) to \( z_{t,m} \) is evenly discretized and \( p_{t,1} + 1 = p_{t,1} = \delta t \) for \( j = 1 \ldots n \).

\[
P = \{p_j = [p_{t,j}, p_{x,j}, p_{y,j}] | j = 1 \ldots n \} \tag{2}
\]

The objective function to be minimized in this problem is the error averaged over all time steps for which fish position measurements were received

\[
J = \frac{1}{m} \sum_{i=1}^{m} e_i \tag{3}
\]

\[
e_i = \sqrt{(z_{x,i} - p_{x,i})^2 + (z_{y,i} - p_{y,i})^2} \tag{4}
\]
In Eq. (4), the variables $p_i/C_{0\ x}$ and $p_i/C_{0\ y}$ refer to the estimated position of the fish just before the position measurement $z_i$ is received.

4. Data set

The specific data set $Z$ used to motivate and validate this work was obtained by Dr. Christopher G. Lowe and Thomas Farrugia in 2008 from a shovelnose guitarfish ($Rhinobatos productus$) actively tracked in the Bolsa Chica Full Tidal Basin, in Southern California (Farrugia et al., 2011). The shovelnose guitarfish was tagged with an acoustic transmitter and was then tracked using an array of static receivers to trilaterate its location as it moved through the bay. The data set consists of latitude and longitude, date and time from one shovelnose guitarfish tracked continuously over a 24 h period (Fig. 1).

Each latitude and longitude measurement pair was time-stamped to the second. In two areas of interest (Figs. 2 and 3) $t_2$ and $t_4$ are both 1000 time-steps away from $t_1$ and $t_3$ respectively; where each measurement received is one time-step. Before being filtered to improve shovelnose guitarfish state estimation, the latitude–longitude coordinates were translated into an $X$–$Y$ cartesian coordinate system with units of meters and the origin located at the latitude $z_{x,1}$ and longitude $z_{y,1}$ 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 (Vincenty, 1975). To minimize the proposed objective function, a multi-state state estimator has been designed (Fig. 4). Sections 5 and 6 describe the different steps of this estimator.

5. Motion behavior

5.1. Behavior characterization

Given a data set $Z$, a set of $b$ characteristic speed behavior are extracted using the standard $k$-means algorithm (Seber, 2008; Spath, 1985). $k$-Means clustering tries to assign each of $m$ measurements to one of $k$ clusters based on distance to the cluster mean. While this clustering problem is NP-hard and computationally expensive, efficient heuristic algorithm exist that converge quickly to a local optimum and are commonly used. Before the $k$-means algorithm can be used, a data set has to be built from the available data that will produce the best results. For this paper, a composite data set $Z$ is constructed using the set of $v_i$ (current speed), $v_{i+1}$ (next speed), $\omega_i$ (current yaw rate), and $\omega_{i+1}$ (next yaw rate). The speed $v_i$ is calculated for each measurement $z_i$ as the distance traveled over the last $T$ seconds to arrive at position $z_{x,i},z_{y,i}$. The yaw rate $\omega_i$ is calculated for each measurement $z_i$ as the difference between the yaw values for
measurements $i$ and $i - 1$ over the last $T$ seconds. This new data set $Z$ is then input into the $k$-means algorithm to extract $b$ clusters. Each of these clusters is considered to be a particular movement behavior, for which a mean and standard deviation in speed and yaw are calculated.

5.2. Behavior estimation

Given a set of $b$ motion behaviors derived from a data set $Z$, the motion behavior at any time can be estimated using a Bayes Filter. Proposed below is one such filter that will later be used to estimate the current behavior for predicting positions in a fish state estimator.

The Bayes Filter is used at each time step $j$ to estimate the probability $p_{i,j}$ that a particle is in the $r$-th behavior, where $r = 1 \ldots b$. For each time step the filter invokes two steps, namely Propagation and Correction.

5.2.1. Propagation

The propagation step is used to predict the likelihoods of the fish being in each of the $b$ behaviors. The prediction is based on how long the fish has had a high likelihood of being in any particular behavior for the most recent time steps, and hence the likelihood of transitioning to a new behavior.

At any given time step, if the probability of a behavior $p_{i,j}$ exceeds a predetermined threshold $\gamma$, it is recognized as the most likely behavior. To keep track of when a fish is acting consistently with a particular behavior, the variable $c$ is defined as the most recent time step at which the fish transitioned to the behavior. That is, $p_{i,j-1} < \gamma$ and $p_{i,j} > \gamma$. Also, the start time associated with this transition to the $r$-th behavior is defined as $u = p_{i,c}$.

At each time step $j$, the Bayes Filter will calculate the time difference between the current time $p_{i,j}$ and $u$. It will then predict the probability of each behavior $p_{i,j+1}$ by summing over the probabilities of transitioning from each behavior at the last time step. For clarity’s sake, the term $P_i$ is used to indicate the probability of a behavior calculated from the prediction step and $P_i$ to indicate the probability after the correction step

$$P_i(\beta_{i,j+1}) = \sum_{s=1}^{b} p_i(\beta_{i,j+1} | \beta_{i,j}) p_i(\beta_{i,j})$$

The conditional probability in Eq. (5), $p_i(\beta_{i,j+1} | \beta_{i,j})$, is calculated using one of three cases depending on the probability of the $s$-th behavior and whether or not $r$ equals $s$

$$p_i(\beta_{i,j+1} | \beta_{i,j}) = \begin{cases} 1 - f(i, u, \sigma_i) & \text{if } s = r \text{ and } p_i(\beta_{i,j}) > \gamma \\ \frac{1}{b} f(i, u, \sigma_i) \prod_{j<i} p_i(\beta_{j}) & \text{if } s \neq r \text{ and } p_i(\beta_{i,j}) > \gamma \\ \frac{1}{b} & \text{else} \end{cases}$$

Case 1: This case occurs when the filter is calculating the likelihood of the fish maintaining a particular behavior $r$ that was determined to be the fish’s behavior in the previous time step, i.e., $r = s$ and $p_i(\beta_{i,j}) > \gamma$.

The conditional probability is calculated based on how long since the fish first transitioned to this behavior, with decreasing likelihood of maintaining the behavior as time passes. It is modeled as one minus the value returned from a sigmoid function $f(i)$, where $f(i)$ is a function of the time passed since first transitioning to the behavior $z_{i-1} = u_i$, the historical average time spent in the behavior $\mu$, and the historical standard deviation in time spent in the behavior $\sigma_i$. This sigmoid function is calculated as follows:

$$f(i; u_i, \sigma_i) = \frac{1}{1 + e^{-(z_{i-1} - u_i)/\mu}}$$

$$\mu = 3600 \frac{24}{b}$$

$$\sigma_i = 300$$

For the purposes of this work, two assumptions were made to construct this sigmoid function. First, it is assumed that the fish spends an equal amount of time in each behavior. Therefore, $\mu$ is equal to the total time in the data set (24 h) divided by the number of behavior ($b$) multiplied by the number of seconds in an hour (3600). Second, it is assumed from observation that the time the fish stayed in any behavior had a standard deviation set to 5 min, (i.e., $\sigma_i = 300$ s). It will be shown that the algorithm is robust to these two approximations.

Case 2: This case occurs when the filter is calculating the likelihood of the fish transitioning to a behavior $r$ from a different behavior $s$ that was determined to be the fish’s behavior in the previous time step, i.e., $r \neq s$ and $p_i(\beta_{i,j}) > \gamma$.

In this case, it is assumed that there is equal likelihood of transitioning from $s$ to any of the other $b-1$ states. Hence the likelihood of transitioning from $s$, i.e., $f(s)$, is divided by $b-1$ to produce the resulting conditional probability.

Case 3: For cases when no behavior was estimated to be of high likelihood in the previous time step, i.e., $\forall s \in [1,b], p_i(\beta_{i,j}) < \gamma$, the conditional probability assigns equal likelihood to each of the behaviors. That is, if neither of the two cases apply, then the conditional probability equals one divided by the number of behaviors.

5.2.2. Correction

For time steps in which a new measurement becomes available ($3 \leq i \leq b$, $p_{i+j} = z_i$), the Bayes Filter will perform a correction step to take into account the new measurement. Bayes rule is used for the correction step as shown in Eq. (8)

$$P_i(\beta_{i,j+1} | z_0, z_1, \ldots, z_i) \approx P_i(\beta_{j+1} | z_i)$$

$$P_i(\beta_{i,j+1} | z_0, z_1, \ldots, z_i) = P_i(\beta_{i,j+1} | z_i)$$
\[ P(\beta_{j+1}) = \frac{P(z_j, \beta_{j+1}) P(\beta_{j+1})}{P(z_j)} \]  

where

\[ P(z_j) = \sum_{r=1}^{R} P(z_j | \beta_{j+1}) P(\beta_{j+1}) \]  

In Eq. (10), the predicted probability \( P(\beta_{j+1}) \) is calculated as shown in Eq. (6). The denominator is calculated as shown in Eq. (11), which ensures all probabilities sum to 1.

The main term is the conditional probability \( P(z_j | \beta_{j+1}) \), which is the likelihood of obtaining the current position measurement assuming the fish is in behavior \( r \). This probability is calculated by comparing the current estimated speed of the fish \( v_{j+1} \) with the expected speed \( \overline{v}_r \) if the fish is in the \( r \)-th behavior. The difference in these speeds is passed through a Gaussian function with a standard deviation \( \sigma_{v,r} \) associated with the error variance of the measurements.

\[ P(z_j | \beta_{j+1}) = \frac{1}{\sqrt{2\pi \sigma_{v,r}^2}} e^{-\frac{(v_{j+1} - \overline{v}_r)^2}{2\sigma_{v,r}^2}} \]  

6. Fish state estimation

To estimate the location of a tagged individual both during and between acoustic position measurements of a data set \( Z \), several filtering methods were investigated. First, as a baseline approach, state estimates were calculated by interpolating positions from the previous two measurements. Second, a standard Particle Filter (PF) was used in which a random walk was used to propagate particles during the prediction step, and the measurements from \( Z \) were used for the correction step. Third, a modified Particle Filter termed the Behavior Based Localization Algorithm (BBLA) was developed. In the prediction step of this new estimator, each particle’s fish behavior is first estimated. Then, the behavior’s speed characteristics are used in a motion model to propagate that particle’s state forward. Described below are these different approaches to state estimation.

6.1. Alg 1: linear interpolation

The first algorithm predicts the fish’s position based solely on the last two position measurements. In this implementation, the position is predicted for each time stamp \( z_{j+1} \) that a new measurement is received. This allows a comparison between the predicted position \( x_{j+1}, y_{j+1} \) and actual measurements \( x_{j+1}, y_{j+1} \).

For each measurement \( i \) in \( Z \), the speed \( v_i \) and yaw \( \theta_i \) of the fish are calculated based on the previous measurements \( i-1 \) and \( i-2 \). The variable \( \Delta t_{i-1} \) is the time difference between previous measurements, i.e., \( \Delta t_{i-1} = z_{i-1} - z_{i-2} \).

\[ \left| \frac{v_i}{\Delta t_{i-1}} \right| = \sqrt{ \left( z_{i-1} - z_{i-2} \right)^2 + \left( z_{i+1} - z_{i-1} \right)^2 } \]  

\[ \left| \frac{\theta_i}{\Delta t_{i-1}} \right| = \frac{a \tan(2 \Delta t_{i-1} - z_{i+1} - z_{i-1})}{\Delta t_{i-1}} \]  

The fish position at any time is then predicted using speed and yaw. For example, to predict the position at time \( z_{j+1} \), the following transition model is used:

\[ p_x^j = x_{j+1} + v_x \Delta t \cos(\theta_i) \]  

\[ p_y^j = y_{j+1} + v_x \Delta t \sin(\theta_i) \]  

To obtain predicted positions at times after \( z_{j-1} \) but before \( z_{j+1} \), a smaller value for \( \Delta t \) can be used.

6.2. Alg 2: basic Particle Filter

The second algorithm estimates the fish’s position at discrete time steps using a Particle Filter. To represent the current belief of the fish’s state, the Particle Filter uses a distribution of state estimates, called particles. Each particle includes a weight that reflects the likelihood that the particle’s state is the actual state. At each time step iteration of the algorithm, two steps are applied to each particle in the distribution. The first step, Prediction, propagates the particle state estimates forward in time according to a motion model. The second step, Correction, occurs only at time steps corresponding with the reception of new measurements. During the Correction step, weights are calculated for each particle based on how closely the predicted position of the particle matches the measured position. Then, a new distribution of particles is selected randomly from the previous set, giving greater chance of selecting particles with higher weights. After the Correction step, the state estimate can be calculated by averaging over all particle state estimates. A thorough explanation of the Particle Filter can be found in Thrun et al. (2005).

For the Particle Filter implementation described here, a set of \( q \) particles is used. Each particle consists of an estimated state including 2D position \( x, y \), speed \( v \), yaw \( \theta \), and weight \( w \). The particle distribution is initialized by randomly selecting particle positions from a 2D gaussian distribution with a mean equal to the first measurement location \( (x_{0}, y_{0}) \) and standard deviation \( \sigma_{z} \). In this case, the variable \( \sigma_{z} \) is the standard deviation in position of the acoustic system used to measure the fish’s position. The value for \( \sigma_{z} \) used in this paper is 2.32 m (Espinoza et al., 2011).

Once initialized, the algorithm iterates at evenly spaced time steps of size \( \Delta t \) by calling the two following steps.

6.2.1. Prediction

At each time step \( j \), the speed \( v_{k,j} \) and yaw \( \theta_{k,j} \) of each particle \( k \) are first calculated based on the previous values \( v_{k,j-1}, \theta_{k,j-1} \)

\[ v_{k,j} = v_{k,j-1} + \sigma_{z} \times \text{randn}() \]  

\[ \theta_{k,j} = \theta_{k,j-1} + \sigma_{\theta} \times \text{randn}() \]  

The variables \( \sigma_{z} \) and \( \sigma_{\theta} \) are the standard deviation of the respective measured speeds and orientations of the fish between time steps \( 0 \) and \( j \) respectively. The function \( \text{randn}() \) returns a zero mean, variance of 1 Gaussian distributed pseudo-random number.

The position states \( (x_{k,j}, y_{k,j}) \) of each particle \( k \) are then calculated using the speed and yaw. The variable \( \Delta t \) is the time difference between time steps

\[ x_{k,j} = x_{k,j-1} + v_x \Delta t \cos(\theta_{k,j}) \]  

\[ y_{k,j} = y_{k,j-1} + v_x \Delta t \sin(\theta_{k,j}) \]  

6.2.2. Correction

When a new measurement \( z_{j} \) is received, a weighted resampling of the particles occurs. First, the weight of each particle is calculated by comparing the particle’s position \( (x_{k,j}, y_{k,j}) \) with the sensor measurement \( (x_{z,j}, y_{z,j}) \). The distance between these two positions \( \text{dist}_{z,j} \) is passed through a Gaussian function to determine the particle weight \( w_{k,j} \). As defined above, the variable \( \sigma_{z} \) is the standard deviation in position of the acoustic system used to measure the fish’s position.

\[ \text{dist}_{z,j} = \sqrt{ (x_{z,j} - x_{k,j})^2 + (y_{z,j} - y_{k,j})^2 } \]  

\[ w_{k,j} = \frac{1}{\sqrt{2\pi \sigma_{z}}} e^{-\frac{(\text{dist}_{z,j})^2}{2\sigma_{z}^2}} \]
6.3.1. Propagation
are calculated based on the previous values estimates, a Bayes Filter is used (see Section 5.2).

\[ p^x_k = p_{x,j} = \frac{\sum_{k=1}^{q} w_k x_j}{\sum_{k=1}^{q} w_k} \]

\[ p^y_k = p_{y,j} = \frac{\sum_{k=1}^{q} w_k y_j}{\sum_{k=1}^{q} w_k} \]

6.3. Alg 3: behavior based localization algorithm

The Behavior Based Localization Algorithm is similar to Algorithm 2, but also estimates the fish’s motion behavior for each particle. In this algorithm, each particle consists of a position \(x, y\), speed \(v\), yaw \(\theta\), behavior \(r\), and weight \(w\). To update behavior estimates, a Bayes Filter is used (see Section 5.2).

6.3.1. Propagation
At each time step \(j\), the speed \(v_{k,j}\) and yaw \(\theta_{k,j}\) of each particle \(k\) are calculated based on the previous values \(v_{k,j-1}\), \(\theta_{k,j-1}\). The variables \(\sigma_v\) and \(\sigma_\theta\) are the standard deviations of the speed and yaw of the particle’s current behavior \(r\)

\[ v_{k,j} = v_{k,j-1} + \sigma_v \cdot \text{randn()} \]

\[ \theta_{k,j} = \theta_{k,j-1} + \sigma_\theta \cdot \text{randn()} \]

At each time step \(j\), the position \((x_{k,j}, y_{k,j})\) of each particle \(k\) is then calculated using speed and yaw. The variable \(\delta t\) is the time difference between time steps

\[ x_{k,j} = x_{k,j-1} + v_{k,j} \delta t \cos(\theta_{k,j}) \]

\[ y_{k,j} = y_{k,j-1} + v_{k,j} \delta t \sin(\theta_{k,j}) \]

6.3.2. Correction
When a new measurement \(z_i\) is received, the weight for each particle is calculated and the particles are resampled in the same way they are for Algorithm 2 (Eq. 21).
To determine the estimated fish position, this algorithm calculates a position estimate for each of the \(b\) different behavior. For the \(r\)-th behavior, the position estimate is calculated as the weighted average of the associated particle positions. For example, Eq. (29) is used to calculate the fish position at time \(p_{r,j}\) associated with behavior \(r\) just before a measurement \(z_i\) the position estimate is calculated below

\[ p^x_{r,j} = p_{x,r,j} = \frac{\sum_{k=1}^{q} \eta_{r,k} w_k x_k}{\sum_{k=1}^{q} \eta_{r,k} w_k} \]

\[ p^y_{r,j} = p_{y,r,j} = \frac{\sum_{k=1}^{q} \eta_{r,k} w_k y_k}{\sum_{k=1}^{q} \eta_{r,k} w_k} \]

In this case the variable \(\eta_{r,k} = 1\) if \(P(p_{r,k,j}) > P(p_{s,k,j})\) for all \(s \neq r\) for particle \(k\), and 0 otherwise. The behavior \(r^*\) with the position estimate closest to the most recent measurement is set as the filter’s current position estimate. For the time step \(j\) just before a measurement \(z_i\) is obtained, the position estimate is given in Eqs. (31) and (32)

\[ p^x_{r^*,j} = p_{x,r^*,j} \]

\[ p^y_{r^*,j} = p_{y,r^*,j} \]

7. Results

7.1. Behavior characterization
To produce the behavior needed for the BBLA algorithm the \(T\) data set, composed of \(v_y, v_{x,T}, \theta_{T},\) and \(\alpha_{T}\), was clustered over all dimensions with the \(k\)-means clustering algorithm. Clustering performance was measured according to the average standard deviation of speed and yaw rate associated with each cluster. For example, a cluster of measurements with low standard deviation in speed represents a set of measurements with approximately the same speed and we associate this cluster of data with a movement behavior.
Clustering performance was investigated while varying two parameters, namely \(b\) the number of behaviors (i.e., clusters) and \(T\) the size of the time window within which speed and yaw rate are averaged. Shown in Figs. 5 and 6 are the average standard deviations as a function of \(b\) and \(T\). Clearly, \(T\) affects performance more than \(b\) for this data set, and a value of \(T=5\) min provides minimal standard deviation while still allowing for speed calculations with relatively recent data.

The number of clusters (\(b\)) did not have a significant effect on the average standard deviations, indicating that an optimal number of behaviors was not present. However, it did have some affect on the average standard deviation in cluster speed. Based on Fig. 5 the
optimum tradeoff between minimum number of clusters and low
standard deviation appears to be at three clusters. This also indicates
that if there is an expected or desired number of behavioral modes
identified in previous scientific observations, the $k$-means algorithm
can be used to extract useful characteristics (e.g., mean and standard
deviation of speed and yaw) for each behavior. Those characteristics
can then be used in the Bayes Filter described in Section 5 to
estimate the current behavior of the fish as a function of time (Fig. 9).

Fig. 6. Average standard deviation in cluster yaw rate.

Fig. 7. Average error of the BBLA for varying values of $\gamma$.

Fig. 8. Speed and closest behavior over time.
7.2. Behavior estimation

Validating the effectiveness of the Bayes Filter is difficult with no truth data for comparison. To illustrate the filter behaves as expected, the behavior \( r \) whose speed \( v_r \) most closely matches the current speed \( v_j \) at each time step \( j \) was compared with the estimated behavior for each time step. For the case when \( b = 3 \), this is plotted in Fig. 8. In the bottom graph, the values 1, 2, and 3 correspond to each of the three behaviors for the value of \( b \) that was picked in order of lowest (behavior 1) to highest (behavior 3) mean speed. Also at time steps \( t_1 - t_4 \) (for which the shovelnose guitarfish’s position is graphed in Figs. 2 and 3), the speed of the closest behavior at those time steps corresponds well with the speed during these time steps. Between \( t_1 \) and \( t_2 \), the shovelnose guitarfish had a low speed and traveled a small distance whereas between \( t_3 \) and \( t_4 \) the shovelnose guitarfish had a large speed and traveled a larger distance.

Using the closest behavior as a reference, one can also observe the filter’s estimated probability of each behavior at each time step (Fig. 9). Between time steps \( t_1 \) and \( t_2 \), the probability of behavior 2 and 3 are very low and the probability of behavior 1 is close to 100%. Similarly, the closest behavior in Fig. 8 is behavior 1 at both those time steps. Also, between time \( t_3 \) and \( t_4 \) the probability of behavior 3 is very high (and 1 and 2 are very low) just as the closest behavior is behavior 3.

7.3. Fish state estimation

Evaluating the effectiveness of the three localization algorithms without truth data is difficult for practical reasons, so the ability of the algorithms to predict the fish position states was tested. This ability is also important in real-time tracking applications, e.g., in tracking fish with AUVs. To evaluate the proposed Behavior Based Localization Algorithm (BBLA) ability to estimate fish position, the error and cost function from Eqs. (4) and (3) were calculated when each of the three algorithms (BBLA, PF, SP) were applied to the shovelnose guitarfish data set.

Before comparing the BBLA with the basic Particle Filter (PF) and the Simple Prediction (SP) method, near optimal parameters for the BBLA were determined. These parameters included the size of the speed time average window \( T \), the number of behavior \( b \), the time step size \( \Delta t \), the number of particles \( P \), and the behavior threshold \( \gamma \) (Table 1).

In order to tune the variable \( \gamma \), the PF and BBLA were both run with varying values for \( \gamma \). It was observed that the std dev of the localization error was minimal across the entire data set. For example, the BBLA algorithm showed little variation in performance, i.e., error standard deviation = 0.0035 m, when \( \gamma \) was varied between 0 and 1 (Fig. 7).
It was observed that regardless of other parameters, $\Delta t = 1$ and $P = 150$ proved ideal for minimizing error. However, of interest was how values for $T$ and $b$ affected localization error. To decide which values to use the standard deviation of speed and yaw rate of the clusters as a function of $T$ and $b$ (Figs. 5 and 6) were considered. The value of $T = 5$ provides a good balance between low standard deviations and low time average window. The value of $b = 3$ provides a tradeoff between low standard deviations and a minimum number of clusters.

It can be observed the BBLA and PF approaches outperformed the SP method which had a mean error of 1.34 m. Algorithm 2, the basic Particle Filter (PF), produced a mean error of 1.21 m. The third algorithm, the Behavior Based Localization Algorithm (BBLA), produced the lowest mean error of 1.00 m (Table 2).

To demonstrate the robustness of the BBLA with respect to training data size, a 10-fold cross validation (Fig. 12) was performed. It can be seen that the BBLA has smaller average error relative to the PF for each proportion of the data set used as validation except for the very first percentile.

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<th>Table 1</th>
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<td>Values of parameters.</td>
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<tr>
<td>Parameter</td>
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<td>Mean and max error for the three fish state estimation algorithms.</td>
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![Fig. 11](image1.png) Close-up of Fig. 10 around time-steps t3 and t4.

![Fig. 12](image2.png) Ten-fold cross-validation run of PF and BBLA for $T = 300$ and $b = 3$. 
When comparing the errors, it is useful to see the percent differences between the algorithms. The PF improved compared to the SP method by reducing the max error by 49.86% and the mean error by 9.85%. The BBLA improved compared to the SP method by reducing the max error by 49.74% and the mean error by 25.65%. It improved over the PF by reducing the mean error by 17.52%, but increased the max error by 0.23%.

Of greatest benefit is the use of the filter when an outlier acoustic measurement occurs or during long periods of no acoustic signal receptions. In these cases, the filter ability to better estimate fish motion and hence position using the behavioral modes becomes clearer. In one case just before time 03 the BBLA error dropped over 45% when compared to the PF method (Table 2 and Fig. 11). Another case occurred at 23:43:07 on 9/25/08 where the BBLA error dropped over 10% when compared to the PF (Fig. 13).

8. Conclusion and future work

In this paper a new fish localization algorithm is presented that produces higher temporal resolution and improved state predication when compared with interpolating raw acoustic position measurements. It was shown that using an algorithm that meshed a Bayes Filter for estimating motion behaviors 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 measurements and using a basic Particle Filter. While the algorithm presented in this paper yielded positive results predicting positions only of a shovelnose guitarfish, the algorithm is not specific to this particular fish. Most fish species follow their own behavioral patterns, but the algorithms presented here can be applied to different species and allow characterization of 2D motion behaviors for each species.

Ideas to improve this algorithm include calculating a mean and standard deviation for the actual amount of time the fish spends in each behavior. Moreover, future work includes implementing such algorithms within AUV based fish tracking systems where the algorithm can be run in real time to improve fish state estimation for autonomous tracking and following.

Acknowledgments

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References


