Increasing Persistent Navigation Capabilities for Underwater Vehicles with Augmented Terrain-Based Navigation

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***Abstract*—Accurate and energy-efficient navigation and localization methods for autonomous underwater vehicles continues to be an active area of research. As interesting as they are important, ocean processes are spatiotemporally dynamic and their study requires vehicles that can maneuver and sample intelligently while underwater for extended durations. In this paper, we present a new technique for augmenting terrain-based navigation with physical water data to enhance the utility of traditional methods for navigation and localization. We examine the construct of this augmentation method over a range of deployment regions, e.g., ocean and freshwater lake. Data from field trials are presented and analyzed for multiple deployments of an autonomous underwater vehicle.**

I. INTRODUCTION

Effective study of ocean processes requires long-term sampling efforts (weeks to months) that match the duration of the respective oscillation patterns. This requires persistent, autonomous underwater vehicles that have similarly long deployment durations, and specifically, vehicles that can remain submerged for data collection for long periods of time, e.g., [1]- [4]. Our work is motivated by the desire to enable intelligent data collection of complex dynamics and processes that occur in *coastal* ocean environments to further our understanding and prediction capabilities. Of particular interest is the formation and evolution of Harmful Algal Blooms (HABs) in the Southern California Bight (SCB); an oceanic region contained within $32°$ N to $34.5°$ N and $-117°$ E to $-121°$ E. This region is under continued study to uncover the connections between small-scale biophysical processes and large-scale events related to algal blooms, specifically blooms composed of toxin-producing species (i.e., HABs) [5]- [7].

The spatiotemporal dynamics of the ocean environment, coupled with limited communication capabilities, make navigation and localization difficult, especially in coastal regions where the majority of interesting phenomena occur. To add to this, the interesting features are themselves spatiotempoally dynamic, and effective sampling requires a good understanding of vehicle localization relative to the sampled feature. Furthermore, these interesting phenomena are usually identified by unique *features* in the ocean, e.g., significant bathymetric relief, an unstratified water column, or significantly different physical water parameter values. Here, we are interested in the utility of these unique features to aid in localization and navigation for underwater vehicles.

Fig. 1. YSI EcoMapper Autonomous Underwater Vehicle executing a mission off the coast of Santa Catalina Island.

Underwater vehicles, like the YSI EcoMapper seen in Fig. 1, commonly perform underwater navigation via dead reckoning using an accelerometer, magnetometer and depth sensor for feedback. However, these instruments are subject to large drift, leading to unbounded uncertainty in location. When confronted with the dynamic environment of the ocean, a state estimate of location can deviate significantly from the actual location; sometimes on the order of kilometers. Two common methods of correcting this issue are 1) surface more frequently for a GPS fix, or 2) integrate more accurate, energy intensive sensors, such as Doppler velocity loggers (DVLs). Both of these methods have drawbacks. Continually surfacing for a GPS fix takes away from sampling time and requires that more energy be used for communications. Surfacing also poses a physical threat to the vehicle, as it might accidentally surface in a hazardous location,

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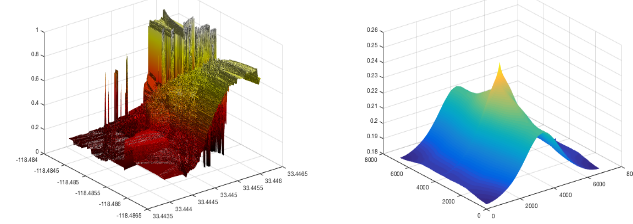
e.g., a shipping lane. Using more powerful sensors consumes the finite energy supply of an AUV faster and significantly reduces the deployment duration. To optimize time spent collecting data with these vehicles, it is desirable to find alternative means of reducing position uncertainty while underwater.

Here, the proposed method for increasing navigational accuracy and reducing uncertainty in navigation is implementing Terrain-Based Navigation (TBN) in an underwater environment. Prior to satellite-based navigation, e.g., GPS, long-distance navigation systems were developed for missiles [8]. Data from an embedded altimeter were compared to ground elevations that were provided in a stored map or look-up table. The navigational accuracy of this method is dependent upon both the resolution of the underlying topographic map and the accuracy of the elevation measurement; each very good for terrestrial applications. This system became redundant after the introduction of GPS, although it is still a useful navigational aid for GPS-denied environments, e.g., underwater. Until recently, the utility of this Terrain-Based Navigation (TBN) for underwater vehicles was low due to the poor resolution of bathymetric maps. Updated bathymetry maps with higher resolution provide motivation for revisiting the application of this method for low-power, accurate navigation underwater, see e.g., [9].

Even with higher resolution bathymetry maps, traditional TBN alone can result in significant navigational error, especially in regions of little to no vertical relief. To enhance the ability to navigate and localize, we developed an augmented TBN that incorporates physical science data, i.e., water parameters such as temperature, salinity, pH, etc., to enhance the topographic map that the vehicle uses to navigate under the traditional TBN framework [10]. In this navigation scheme the bathymetry data are combined with the physical science data to enrich the uniqueness of the underlying *terrain* map, see e.g., Fig.2. This method of localization has been evaluated with data gathered at multiple locations in both freshwater lakes and oceanic environments. Results from a deployment in Big Fishermans Cove, Santa Catalina Island is presented in [10]; these and other preliminary results from our Augmented Terrain Based Navigation (ATBN) have been promising.

The primary issue that arises in using the proposed ATBN methodology is that the physical water parameters, e.g., temperature and salinity, are spatiotemporally dynamic. Thus, a generated *terrain* map based solely or partially on these variables will change in space and time. An investigation of the spatiotemporal variability within the proposed method is currently under investigation by the authors and is ongoing work. The focus of this paper is to describe the proposed technique and present initial results in creating augmented terrain maps for use in navigation and localization.



(a) (b)

Fig. 2. Example of an augmented *terrain* map using a combination of science parameters along with bathymetry information. Fig. (a) is the resulting terrain map, and Fig. (b) is the auto-correlogram. The data for the figures was collected off Santa Catalina Island, CA.

II. BACKGROUND

A. Terrain-Based Navigation

A detailed survey of research and current challenges in underwater navigation, summarizing existing work on TBN for underwater vehicles, is provided in [11]. One clearly identified shortcoming of TBN in the aquatic environment is the lack of accurate, high-resolution maps of the sea floor in many regions. Additionally, sensor limitations, especially the limitations of optical range sensors, substantially restrict TBN underwater. In [11], it is concluded that improved navigation will enable new missions that would previously have been considered infeasible or impractical.

Recent work by Lagadec on TBN under ice [12] has demonstrated the feasibility of using a particle filter for long term glider navigation. Lower relief maps of regions above the arctic circle with a resolution of 2 km were sufficient to navigate with reasonable accuracy ($\sim$ 1 km accuracy, with a mean accuracy of approximately 8 km in one simulation). The study suggests that for real deployments, technological advances would be necessary to achieve the required navigation performance. However, higher relief bathymetric maps could facilitate the implementation of a TBN that operates online, in real time. The primary limitation of the technique presented in [12] was the lack of an accurate terrain map, which does not invalidate the methodology used. A number of other studies have utilized particle filters as part of a TBN framework for underwater vehicles [12]-[15]. The particle filter is suitable as a solution to the TBN problem because it is probabilistic (and therefore captures environmental uncertainty), and because it naturally incorporates the property that the longer a path is traversed, the more likely a single solution will emerge.

B. Improving TBN

To further improve TBN, a method of creating an augmented terrain map that combines both bathymetric information and physical water data collected was proposed and tested, with results presented in [10]. The assumption that including physical water data into the terrain map provides a reliable model comes from the concept of Environmental or Ecological Niche Models. Ecological Niche Modeling is derived from one of the primary goals of ecology, which is to map species distribution over geographic ranges and be able to use predictive models to infer where various species are likely to be found [16]- [19]. Environmental niche modeling uses a wide range of data to generate a map of a locale showing only chemical and physical parameters that have either been measured or interpolated from direct measurements [20]. Specifically, niche modeling is a method to classify geographic locales as either being habitable or inhabitable by certain species. By monitoring specific physical parameters of an environment and understanding the tolerances of a certain species, it is possible to model where that species will most likely be present [19]- [23]. Here, we hypothesize that these niches may also be utilized for underwater vehicle navigation. At this stage, we will assume that the environment is static in both space and time; however, the spatiotemporal dynamics of observed ecological niches suggests that they exhibit periodicity or a predictable stochastic behavior, see e.g., [24].

III. METHODOLOGY

The basic process for creating a terrain map from the scientific and bathymetry data is to first generate a base map for each data parameter being collected. Then, determine a weighting schema that enables the maps to be brought together via linear combination while maximizing the contrast of the resulting *terrain map*. More specifically, the raw data are first treated for outliers with the k-nearest neighbor technique, and individual scalar fields are created for each data parameter (temperature, pH, turbidity, chlorophyll, blue-green algae, depth and dissolved oxygen). The spaces between data points are filled in by using the bi-harmonic spline interpolation[1]. This method was used because it is also able to extrapolate outside of the convex hull and generate smooth surfaces. The resulting map is a matrix, $\mathbf{X}$, where each element (i,j) corresponds to the coordinate (x,y) where the value was measured. These matrices were normalized by subtracting the minimum value from each element of the matrix, then dividing by the new maximum value.

[1]MATLAB griddata method 'v4'

$$\mathbf{N} = \mathbf{X} - min(\mathbf{X}) \tag{1}$$

$$\mathbf{M} = \frac{\mathbf{N}}{max(\mathbf{N})}, \tag{2}$$

Here $\mathbf{M}$ is the normalized matrix.

Bathymetric and physical water data were gathered on the surface of unique water bodies through multiple deployments of the vehicle. These deployments were performed in different bodies of water: (i) Big Fisherman's Cove, Santa Catalina Island (33°44'N 118°48'W), CA, USA (coastal ocean bay); (ii) Lake Nighthorse (37°13'N 107°55'W), Durango, CO, USA (large fresh water lake); (iii) Monterey Bay (36°48'N 121°47'W), CA, USA (coastal ocean bay). The vehicle navigated on the surface of the water to ground-truth measurements via GPS collecting data referenced to GPS locations. The combination of the parameters with the associated weights provides the "*bumpiest*" scalar field (i.e. the scalar field with the most likelihood that a given trajectory across it is unique with respect to all others). To assess this characteristic, we propose a measure called *global correlation*.

We assume that the lower the spatial auto-correlation, the higher the *randomness* of the spatial field. Auto-correlation of each matrix (equation (2)) is then calculated and its peak value is replaced by 0. The sum of the absolute values of the matrix is the global correlation value. We seek the appropriate parameters for each of the surveyed bodies of water using combinations of physical water parameters and bathymetric information to ensure that each and every spatial path through a water body is defined and unique. Then, we determine similarities among them and the set of coefficients that maximize their variability. We tested two different distributions to find the appropriate weights for the parameters. The first is the Simple Simplex Distribution and the second is the Dirichlet Distribution.

1) Simple Simplex Distribution: Let α=$\{\alpha_1, \alpha_2, \ldots, \alpha_n\}$, where $\alpha_i > 0$, $\sum_{i=1}^{n} \alpha_i = 1$ and n is the number of water parameters, be the set of coefficients that minimizes the spatial auto-correlation. A suitable *terrain* map computed from our proposed approach for navigation and localization is given by $S = \alpha_1 * var_1 + \alpha_2 * var_2 + ... + \alpha_n * var_n$, where S represents a linear combination of the parameters considered. The set of coefficients is obtained using uniformly random sampling from unit simplex [25]. Over a random multinomial probability distribution, an array X=$\{x_1, \ldots, x_{a-1}\}$ with unique entries from a uniformly random sampling is created with values varying among $\{1, 2, \ldots, \text{M}-1\}$, where M is the maximum integer, without replacement. The first value is $x_0 = 0$ and the last is $x_a = M$. Array X is then sorted in ascending order. Let Y={$y_1, y_2, \ldots, y_i, \ldots, y_{M-1}$} with y_i being defined as $x_{i+1} - x_i$, $\forall i \in \{1, 2, \ldots, a\}$. Each entry of array Y is then divided by the sum of all the values of Y so that the new sum is equal to 1.

2) The Dirichlet distribution: Next, a weighting schema for the parameters is determined through Dirichlet Distribution, which is a reference distribution to model vectors of weights adding to 1. It is a probability density function over the simplex and can model prior knowledge of the weights of the parameters. It is defined as:

$$\mathbf{p}(\alpha|\gamma) = \frac{\Gamma(\sum_{i=1}^{n} \gamma_i)}{\prod_{i=1}^{n} \Gamma(\gamma_i)} \prod_{i=1}^{n} \alpha_i^{\gamma_i - 1} \tag{3}$$

where γ is the vector of parameters of the Dirichlet distribution with $\gamma_i > 0$; α={$\alpha_1, \alpha_2, \ldots, \alpha_n$}, $\alpha_i > 0$ and $\sum_{i=1}^{n} \alpha_i = 1$, is the vector in the n-dimensional probabilistic simplex representing the weights of the parameters; n is the number of parameters to be considered for the generation of the scalar fields and Γ denotes the gamma function. The individual scalar fields from each parameter are brought together via a linear combination with their respective weights to create a single scalar field that is the terrain map. This map is given by $S = \alpha_1 * var_1 + \alpha_2 * var_2 + \ldots + \alpha_n * var_n$. The weighting schema is iterated on thousands of times until the global correlation converges to a minimum value.

3) Linear Combination: For all variables, let α={$\alpha_1, \alpha_2, \ldots, \alpha_n$} be the set of coefficients for each science data considered for this study. A suitable *terrain* map computed from our proposed approach for navigation and localization is given by the linear combination S presented in Equation. 4

$$\begin{aligned} S =& \alpha_1 * temperature + \alpha_2 * pH + \\ & \alpha_3 * turbidity + \alpha_4 * chlorophyll + \\ & \alpha_5 * depth + \alpha_6 * dissolved\_oxygen + \\ & \alpha_7 * salinity \end{aligned} \tag{4}$$

Here, S represents a linear combination of the science parameters considered, α is the set of coefficients that minimizes the spatial auto-correlation.

We compared the global correlation value considering: (i) only bathymetric information, (2) only science parameters, (3) science parameters and depth combined for each deployment location.

The results showed that bathymetric information is a viable approach for creating terrain maps. Here, we examine bathymetric information using the same methods used for addressing questions 1, 2 and 4. Finally, the fourth and last test is addressed by combining the bathymetric infomation with the science parameters as a new approach. Equation 4 is extended to include depth as another variable and analyzing the effect of the bathymetry structure.

Any traditional TBN algorithm can then be applied to this augmented *terrain* map. It is also assumed that the combination of multiple parameters will produce a terrain map that is more unique than a terrain map composed of a single parameter; thus, improving the ability to reduce navigation uncertainty while underwater. The complete technique of ATBN would involve surveying an area, determining the weights of data parameters, and generating a *terrain* map through post processing. The vehicle is then provided with the *terrain* map and weightings to perform ATBN during subsequent deployments. Research into how to efficiently update this underlying map is presented in [26].

IV. RESULTS

Using the data from on-board sensors, terrain maps for localization and navigation were generated for use in later missions. Preliminary results using bathymetric data in [27] showed that global correlation is low. When physical water parameters are combined with bathymetric information instead of using either one independently, a lower global correlation value is obtained. Results in different bodies of water are shown in this section.

1) Big Fisherman's Cove, Santa Catalina Island, California: Depth and temperature are the most significant parameters in the ocean, in the case of Big Fisherman's Cove, Santa Catalina Island, California, USA, when the aim is higher variability. Salinity represented 0.43% of importance in generating the most adequate scalar field, while temperature represented 18.7%, turbidity 0.26%, depth 80.6% and 0.01% for the remaining variables. Figure 3 shows the auto-correlogram of the scalar field and figure 4 show the actual scalar field for the surveyed area at Big Fisherman's Cove.

TABLE I
MINIMUM AND MAXIMUM VALUES OF THE PARAMETERS CONSIDERED AT BIG FISHERMAN'S COVE, SANTA CATALINA ISLAND.

Parameter	Minimum	Maximum
Temperature	21.7	23.64
Salinity	5.99	34.01
pH	8.16	8.56
Dissolved Oxygen	8.12	9.66
Turbidity	0	4.99
Depth	1	29.99
Chlorophyll	9.7	47.7

2) Lake Nighthorse, Colorado: Depth and temperature are the most significant parameters in the case of Lake Nighthorse, Durango, Colorado, USA (large fresh water lake) when the aim is higher variability. Depth represented 69% of importance in generating the

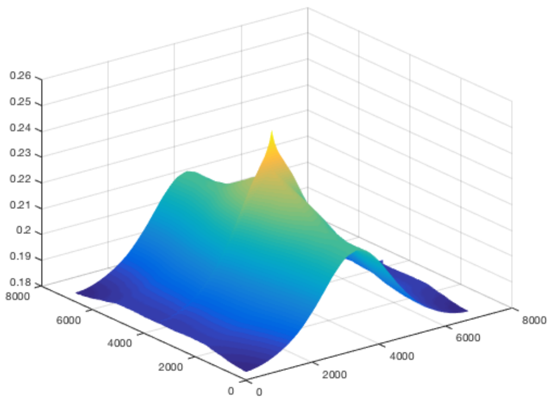


Fig. 3. Auto-correlogram of the scalar field at Big Fisherman's Cove, Santa Catalina Island.

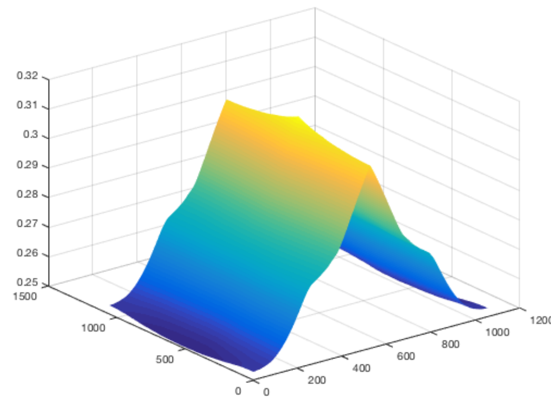


Fig. 5. Auto-correlogram of the scalar field at Lake Nighthorse, CO.

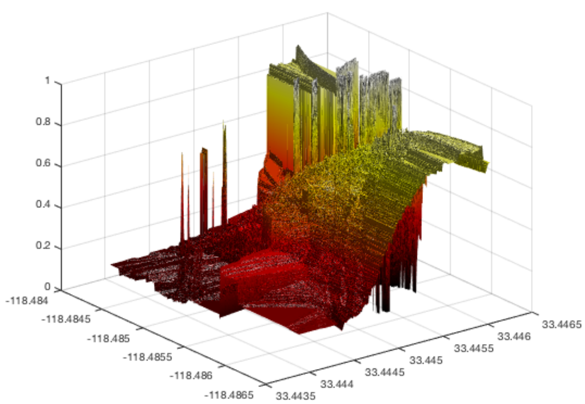


Fig. 4. Scalar field map at Big Fisherman's Cove, Santa Catalina Island.

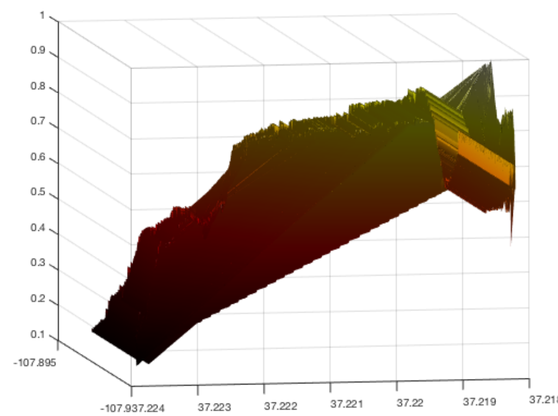


Fig. 6. Scalar field map at Lake Nighthorse, CO.

most adequate scalar field, while temperature represented 30%, and 1% for the remaining variables. Figure 5 show the auto-correlogram of the scalar field and figure 6 show the actual scalar field for the surveyed area at Lake Nighthorse.

TABLE II
MINIMUM AND MAXIMUM VALUES OF THE PARAMETERS CONSIDERED AT LAKE NIGHTHORSE, CO.

Parameter	Minimum	Maximum
Temperature	12.9	13.02
pH	8.32	8.71
Dissolved Oxygen	8.39	8.47
Turbidity	0.8	3.9
Depth	6.71	39.53

3) Monterey Bay, California: Depth and temperature are the most significant parameters in the ocean, in the case of Monterey Bay, CA, USA, when the aim is higher variability. Depth represented 94.1% of importance in generating the most adequate scalar field, while temperature represented 5.8% and 0.1% for the remaining variables. Figure 7 show the auto-correlogram of the scalar field and figure 8 show the actual scalar field for the surveyed area at Monterey.

Results showed that for coastal ocean bay, as seen at Big Fisherman's Cove and Monterey Bay, in California, USA, the parameters depth, temperature and salinity are among the most important ones. The importance is due to the effect on the global autocorrelation that becomes lower when these parameters have a certain weight in the construction of the scalar field.

V. CONCLUSION

The developed approach is an alternate way of targeting sample acquisition or navigating through space,

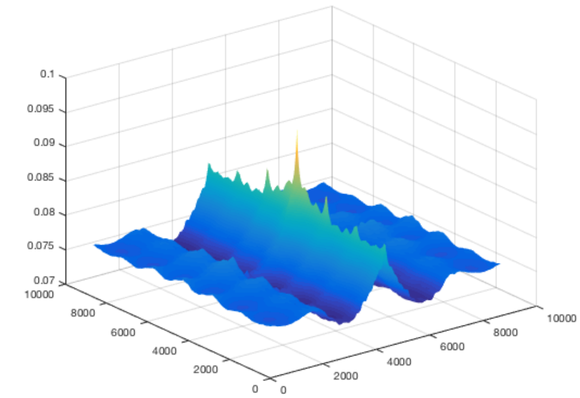


Fig. 7. Auto-correlogram of the scalar field at Monterey Bay, CA

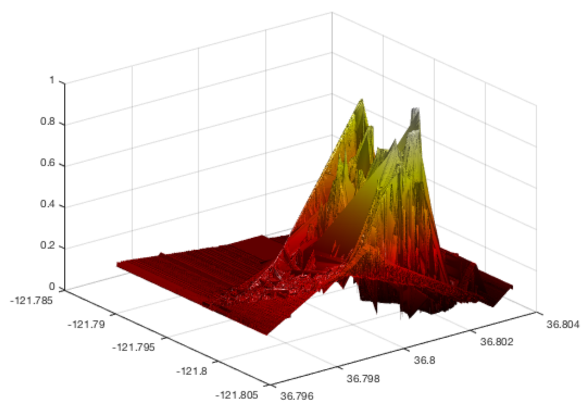


Fig. 8. Scalar field map at Monterey Bay, CA

and relaxes the dependence on geographic coordinates, enabling the design of methods for improving navigation and sampling within a dynamic feature. The utility of our proposed method is currently assessed by localizing a trajectory within a computed augmented terrain map.

A map constructed using *in situ* science data in combination with bathymetry was developed for improving navigation and localization accuracy for aquatic vehicles. When physical data, such as, temperature and salinity, are combined with bathymetric information, the global correlation decreases leading to greater variability and a more suitable map for localization and navigation using the proposed augmented terrain-based navigation technique. Any random trajectory extracted from the terrain map will be unique to that area. This is what makes localization possible though an augmented TBN. In GPS-denied environment, as is the case underwater, augmented TBN with bathymetric and science information poses a promising method for localization and navigation. The utility of TBN for underwater vehicles became valuable with the increase of resolution of bathymetric maps, and as the proposed method further refined these maps with the supplementation of more data.

VI. Future Work

For most ocean science applications, there is a need for underwater vehicles to navigate within a spatiotemporally dynamic environments and to gather data of high scientific value. Therefore, it will be interesting to investigate methods that are able to adequately propagate critical *ecological niches* in a spatiotemporal fashion to maintain the reliability upon then for navigation or relative localization. We consider locations to be drawn from or existing in an environmental space. In this paper, the dependence on geographic coordinates for navigation is relaxed, enabling the deign of methods for improving navigation and sampling within a dynamic feature.

To properly navigate and localize by use of the proposed methodology, we require a real-time state estimation routine to run on-board the vehicle. For this application we have examine the utility of an Unscented Kalman Filter as described below.

A. Unscented Kalman Filter

The Uncented Kalman Filter fuses the measurements from the on-board sensors mentioned above to estimate the position and attitude of the vehicle over time [28]. In this case, we consider a constant velocity model for the vehicle, as that is how the missions are currently executed. This can easily be changed for a specific mission in the future. The UKF is a Bayesian filtering algorithm which employs a statistical local linearization procedure to propagate and update the system state. For nonlinear systems, this approach typically produces significantly more accurate estimates than the analytic local linearization employed by the well-known Extended Kalman filter (EKF) [29]. Our 10×1 state vector is

$$\mathbf{x}(t) = \left[(\mathbf{p}^W(t))^T \quad (\bar{q}_B^W(t))^T \quad (\mathbf{v}^B(t))^T \right]^T \quad (5)$$

where $\mathbf{p}^W(t)$ is the position of the vehicle in the world (UTM) frame, $\bar{q}_B^W(t)$ is the unit quaternion that defines the attitude of the vehicle's body relative to the world frame, and $\mathbf{v}^B(t)$ is the velocity of the vehicle in the body frame. This simple kinematic model is sufficient for this application of long-range planning. A primary motivation for our choice of the UKF is its performance with a more sophisticated (and nonlinear) dynamic model of the vehicle, which we are exploring in a parallel effort. We remark that the UKF we developed works for underwater vehicles operating in three spatial dimensions, and is simplified for our trial here to the 2-D case of operation on the surface of the water.

For our simulation, we assume that the vehicle follows a nominal, bicycle-type trajectory, and that the vehicle's angular rotation rate and linear acceleration are driven by white, zero-mean Gaussian noise processes represented by the vectors $\eta_q(t)$ and $\eta_v(t)$, with covariance matrices $\mathbf{Q}_q$ and $\mathbf{Q}_v$, respectively. The system state evolves in continuous time according to

$$\dot{\mathbf{p}}^W(t) = \mathbf{C}\left(\bar{q}_B^W(t)\right)\, \mathbf{v}^B(t) \tag{6}$$

$$\dot{\bar{q}}_B^W(t) = \frac{1}{2}\Omega\left(\eta_q(t)\right)\, \bar{q}_B^W(t) \tag{7}$$

$$\dot{\mathbf{v}}^B(t) = \eta_v(t) \tag{8}$$

where $\mathbf{C}\left(\bar{q}_B^W(t)\right)$ is the direction cosine matrix corresponding to the unit quaternion $\bar{q}_B^W(t)$, and $\Omega\left(\eta_q(t)\right)$ is the quaternion kinematic matrix, relating the rate of change of the orientation quaternion to the body frame angular velocity [30].

B. Localization with the UKF

We have initially examined the localization of multiple trajectories over a computed scalar field using a UKF. Preliminary localization results using the UKF over our proposed augmented terrain maps have provided promising results that reduce navigation uncertainty as compared with dead reckoning and traditional TBN results. A detailed examination of these results is out of the scope of this paper, but is an area of active investigation. Primarily, we are currently investigating the interplay between the precision and density of the underlying scalar field versus the effect on navigational performance; essentially how dense does the initial survey need to be and how frequent and sparse can updates be.

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