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Autonomous Underwater Vehicle Trajectory Design Coupled with Predictive Ocean Models: A Case Study

Ryan N. Smith*, Arvind Pereira*, Yi Chao‡, Peggy P. Li‡,
David A. Caron†, Burton H. Jones† and Gaurav S. Sukhatme*
*Robotic Embedded Systems Laboratory, Department of Computer Science
†Department of Marine Biology
University of Southern California, Los Angeles, CA 90089
Email: ryannsmi, menezesp, dcaron, bjones, gaurav@usc.edu
‡Jet Propulsion Laboratory, California Institute of Technology 4800 Oak Grove Drive, Pasadena, CA 91109
Email: yi.chao, p.p.li@jpl.nasa.gov

Abstract— **Data collection using Autonomous Underwater Vehicles (AUVs) is increasing in importance within the oceanographic research community. Contrary to traditional moored or static platforms, mobile sensors require intelligent planning strategies to maneuver through the ocean. However, the ability to navigate to high-value locations and collect data with specific scientific merit is worth the planning efforts. In this study, we examine the use of ocean model predictions to determine the locations to be visited by an AUV, and aid in planning the trajectory that the vehicle executes during the sampling mission. The objectives are: a) to provide near-real time, *in situ* measurements to a large-scale ocean model to increase the skill of future predictions, and b) to utilize ocean model predictions as a component in an end-to-end autonomous prediction and tasking system for aquatic, mobile sensor networks. We present an algorithm designed to generate paths for AUVs to track a dynamically evolving ocean feature utilizing ocean model predictions. This builds on previous work in this area by incorporating the predicted current velocities into the path planning to assist in solving the 3-D motion planning problem of steering an AUV between two selected locations. We present simulation results for tracking a fresh water plume by use of our algorithm. Additionally, we present experimental results from field trials that test the skill of the model used as well as the incorporation of the model predictions into an AUV trajectory planner. These results indicate a modest, but measurable, improvement in surfacing error when the model predictions are incorporated into the planner.**

I. Introduction

In this paper, we investigate the use of ocean model predictions to aid in the planning and design of trajectories for AUVs with the goal of tracking and sampling within an interesting and evolving ocean feature. We build upon the three-dimensional (two spatial dimensions plus time) tracking algorithms presented in [1] and [2] by adding another spatial dimension, and considering external forcing through the incorporation of four-dimensional (three spatial dimensions plus time) current predictions, with the intention of generating a mission plan that accurately steers AUVs to locations of high scientific interest. The primary contribution of this paper is the development of an innovative toolchain utilizing pre-existing technologies, and an investigation into the practical application of this technology fusion for use in AUV path planning and trajectory design.

The motivation for using predictive capabilities to design trajectories with the intent of tracking an evolving ocean feature is derived from a practical problem that exists in many coastal communities around the world, and in particular, Southern California. As the rate of urbanization in coastal communities continues to increase, land use and land cover (e.g., a significant increase in impervious surfaces) in these areas are permanently altered. This alteration affects both the quantity of freshwater runoff, and its particulate and solute loadings, which has an unknown impact (physically, biogeochemically, biologically and ecologically) on the coastal ocean [3]. One documented result of these impacts is an increase in the occurrence of algal and phytoplankton blooms. Such biological phenomena are a primary, collaborative research interest of the authors. In particular, we are interested in the assessment, evolution and potential prediction of the blooms that have the potential to include harmful algal species (i.e., Harmful Algal Blooms (HABs)).

The processes leading to the onset, evolution and dissemination of HAB events are still under investigation. The recent development and implementation of an embedded sensor network along the Southern California coast (see e.g., [4], with further details in [5]) provides necessary sensors and infrastructure to facilitate an in-depth, multi-faceted investigation of physical, chemical and biological processes related to HABs in addition to the impacts resulting from urbanization and climate change. Pivotal components of this network are the mobile sensor platforms in the form of autonomous Slocum gliders [6]. Based on their deployment longevity, coupled with the use of multiple gliders (see e.g., [7]), these vehicles can provide an extended spatio-temporal series of observations. Additionally, gliders can be utilized to monitor and track dynamically evolving ocean features that have a lifespan on the order of weeks, i.e., HABs and freshwater runoff plumes [8].

As an overview, the basic mission plan studied in this paper is to track and collect daily information about dynamically evolving ocean processes or features. First, we identify a feature of interest in the Southern California Bight (SCB)§ via direct observation or by use of remotely sensed

§The SCB is the oceanic region contained within 32° N to 34.5° N and −117° E to −121° E data. We then use an ocean model to predict the behavior of this feature, e.g., HAB, over a short time period, e.g., one day. This prediction is used to generate a sampling plan for deployed gliders that steers the vehicles to regions of scientific interest based upon the given feature. Throughout execution of the sampling plan, the collected data are transmitted and assimilated into the ocean model. A new prediction is generated and the process is repeated until the feature dissipates, or is no longer of interest. A long term goal is to collectively implement this and other path planning algorithms, e.g., [9] and [10], via an embedded sensor network (see [4] and [5]) to enable real-time, optimal path planning and trajectory design, based on ocean model predictions and *in situ* measurements gathered by a fleet of mobile sensor platforms to further our understanding of interesting and evolving ocean features and phenomena.

We begin with a brief description of a HAB, the sensor platform and the ocean model considered, and present a review of previous work related to similar problems. Section III contains an in-depth discussion and statement of the path planning problem at hand and describes the three main algorithms designed to obtain a solution; the waypoint selection algorithm for both a boundary tracking and centroid tracking path and OPTA-BLOOM-Pred, which incorporates the four-dimensional ocean current prediction into the sampling mission design. These algorithms are run in simulation, and the results are presented in Section IV. A crucial component to this study is the validation of this toolchain via at-sea trials. Extensive deployment time ($>$ 1500 km traversed over $>$ 100 days at sea in the last nine months) has provided adequate amounts of data for assessment and comparison. Results from recent field experiments can be found in Section V, and show promise for further investigation into the proposed algorithms. We conclude with a summary of the obtained results and comment on the practical application and future implementation of this technology fusion investigation.

II. Background and Motivation

In addition to the study of HABs, we are ultimately interested in understanding the complex dynamics and processes that occur in a *coastal* ocean environment. This research is a collaborative effort between the Marine Biology and Computer Science Departments at the University of Southern California (USC). Together we have formed the Center for Integrated Networked Aquatic PlatformS (CINAPS, pronounced [sin-aps]) to monitor and observe the coastal ecosystems in Southern California through the use of a network of embedded sensor platforms, see [4].

A. Harmful Algal Blooms

Microscopic organisms are the base of the food chain; all aquatic life ultimately depends upon them for food. Of these organisms, there are a few dozen species of phytoplankton and cyanobacteria that can create potent toxins when provided with the right conditions. Harmful algal blooms can cause harm via toxin production, or by their accumulated biomass. Such blooms can cause severe illness and potential death to humans as well as to fish, birds and other mammals. The blooms generally occur near fresh water inlets, where large amounts of nutrient rich, fresh water is deposited into the ocean. This water provides the excess food to support higher productivity and a *bloom* of microorganisms. Impacts of HABs in the SCB are presented in [11], [12].

B. Regional Ocean Modeling System

The predictive tool utilized in this study is the Regional Ocean Model System (ROMS) - a split-explicit, free-surface, topography-following-coordinate oceanic model. ROMS is an open-source, ocean model that is widely accepted and supported throughout the oceanographic and modeling communities. Additionally, the model was developed to study ocean processes along the western U.S. coast which is our primary area of study. The model solves the primitive equations using the Boussinesq and hydrostatic approximations in vertical sigma (i.e., topography following) and horizontal orthogonal curvilinear coordinates. ROMS uses innovative algorithms for advection, mixing, pressure gradient, vertical-mode coupling, time stepping, and parallel efficiency. Detailed information on ROMS can be found in [13] and [14].

The version of ROMS used in this study is compiled and run by the Jet Propulsion Laboratory (JPL), California Institute of Technology. The JPL provides ROMS hindcasts, nowcasts and hourly forecasts (up to 36 hours) for the SCB, [15]. The JPL version of ROMS (see e.g., [16]) assimilates HF radar surface current measurements, data from moorings, satellite data and any data available from sensor platforms located or operating within the model boundary. This ROMS utilizes a nested configuration, with increasing resolution covering the U.S. west coastal ocean at 15 km, the southern California coastal ocean at 5 km, and the SCB at 1 km. The three nested ROMS domains are coupled online and run simultaneously exchanging boundary conditions at every time step of the coarser resolution domain. In addition to the 1 km output, a resampled 2.2 km resolution output is produced, which correlates to the assimilated HF radar grid resolution. This study utilizes this 2.2 km output for our computations. Current velocity predictions are provided at depths of $0, 5, 10, 15, \ldots, 2000$ m, as the bathymetry permits.

A concern with any model is the accuracy and precision of the predictions. Specifically, we are concerned with the spatial structure of the predicted current velocities. ROMS primarily assimilates surface velocities from HF radar data, and it is assumed that forecasting for near-surface velocities are reasonable. However, in areas containing a large vertical complexity of currents, particularly in shelf break regions, ROMS has demonstrated poor prediction capabilities.

It is an area of active research to reduce the uncertainty, improve the performance, and improve the quality and utility of ROMS forecasts. The interaction between this research and ROMS improvement is a two-way street. We need the predictions to design efficient and effective trajectories, and ROMS utilizes the feedback from field deployments to assess the validity of each prediction.

C. Mobile Sensor Platform

The mobile sensor platform used in this study is a Webb Slocum autonomous underwater glider, as seen in Fig. 1, [6]. The Slocum glider is a type of AUV designed for long-term ocean sampling and monitoring [17]. These gliders *fly* through the water by altering the position of their center of mass and changing their buoyancy. Due to this method of locomotion, gliders are not fast moving AUVs, and generally have operational velocities on the same order of magnitude as oceanic currents ($\backsim$ 1 km/hr). The endurance and velocity characteristics of the glider make it a good candidate vehicle to track ocean features which have movements that are determined by currents, and have the capability to remain of scientific interest for weeks at a time.

Fig. 1. HeHaPe, one of two USC Slocum gliders.

Considerable work has been done on the kinematic and dynamic modeling and control of underwater gliders, and we refer the interested reader to [18] and [19] for a detailed treatment of these topics. An example mission for a glider consists of a set maximum depth along with an ordered list of geographical waypoints. An exact trajectory connecting these locations is not prescribed by the user, nor are the controls to realize a final destination. When navigating to a new waypoint, a glider computes a bearing and distance from its current location, then dead reckons (open-loop control implementation) toward the goal location. While underwater, the computed bearing is not altered, the glider must surface to make any corrections or modifications to the planned mission. Upon surfacing and acquiring a GPS fix, the positional error between actual and goal locations is computed. This error is used to estimate any local disturbances (e.g., currents), and is considered when computing the heading and bearing to the next waypoint.

In general, for large-scale, open-ocean, sampling and monitoring missions, as the gliders were designed for, this type of mission planning and execution is reasonable, and robust [17]. Specifically, accuracy and precision are not a priority in such deployment scenarios. However, in a *coastal* setting with the intent to observe an evolving ocean feature, accuracy becomes increasingly important, and is directly related to the size of the feature of interest. With this motivation, we proceed to investigate coupling ROMS 4D velocity predictions with the trajectory design process for feature tracking utilizing gliders.

D. Previous Work

The use of ocean models in AUV path planning is not new, see e.g., [20]-[21]. This approach has been considered in an effort to solve path planning optimization problems. Of particular interest to the AUV community is utilizing ocean currents to minimize energy consumption, thus extending a vehicle's deployment time.

In the specific case of a slow-moving, autonomous glider, time optimization is not an overall consideration. By design, the vehicle is very conservative with respect to its energy consumption. Thus, optimized path planning with respect to time and energy are considered secondary for glider operations. Of primary optimization focus, with direct correlation to ocean currents, is defining a feasible path and improving the accuracy of achieving a goal waypoint. In the presence of a strong current, a glider may be unable to reach a given location. Additionally, complex current structures experienced in a coastal region can vary significantly with time and location, making dead reckoning navigation difficult.

Articles [20]-[21] address the problem of path planning for AUVs in a complex, time-dependent, variable ocean. A main focus is computing energy optimal paths, as the majority of underwater vehicles are propeller-driven, short-duration (< 24 hr) AUVs. A shared downside to these planners is the assumption that the vehicle thrust is assumed constant (e.g., [22], [23] and [24]). This condition is restricting in the case of a general AUV, however this is precisely the situation for a glider. On the other hand, all of these works assume that the vehicle can change its direction while underwater, which is not the case for a glider that requires surfacing to change direction. This is primarily seen in the graph-based, A* approaches seen in [20] and [24]. Additionally, the assumed current velocities are generally coarse resolution averages, as they are estimated from a compiled database, the average conditions as seen over long time periods or are provided only in two spatial dimensions. With ROMS, we have a high-resolution, 4-D current velocity prediction, providing the predicted velocity at more precise locations. The existence of this predictive capability drives us to consider a more continuous approach in path planning for AUVs.

III. Problem Outline

The goal of this paper is to present a path planning solution for tracking an evolving ocean feature using a glider. Preliminary work for this problem has been presented in [1] and [2] by presenting waypoint generation algorithms based on areas of interest within the feature. These articles also presented field deployment and simulation results for the computed missions. Here, we expand these works by incorporating external disturbances (i.e., ocean currents) into the mission planning process. We remark that the intent of this paper is not to create a new simulator for gliders, or AUVs in general, but to demonstrate the integration of existing technologies, with the goal to improve large-scale, coastal ocean monitoring and assessment.

The primary motivation for this work is the study of HABs. Since the biochemical triggers for such events are widely unknown, it is of interest to study oceanic regions before, during and after HAB events occur. From a sufficient time series, gathered at the proper locations, scientists can better assess, and ultimately predict these events.

It is known that an increase in nutrients and/or change in temperature to near-surface waters has a high correlation to the onset of a phytoplankton bloom. Events such as storm river runoff, coastal upwelling or cold core eddys are features of interest that may lead to a bloom event. Here, we consider our feature of interest to be a fresh water runoff plume from a river discharge. Depending on the feature considered, different locations within that feature may be of interest, e.g., its boundary or extent, subsurface chlorophyll maximum, salinity minimum, its centroid, etc. In this paper, we consider the centroid and the boundary of the extent of the plume as two proxy areas of interest. Similar algorithms to those presented can consider the other sampling locations.

Given a freshwater plume, we are interested in designing missions for gliders to track and sample along the path of the centroid and boundary of the feature. We assume that we have at least two vehicles to perform the missions; one centroid tracker and one boundary tracker. Due to the large amounts of chromophoric dissolved organic matter, a freshwater plume can be easily depicted from satellite imagery. Additionally, this feature directly follows a rain event, and the discharge location (i.e., river mouth) is well-known. Thus, we may assume that we can delineate the extent of a freshwater plume at a given point in time.

Being less dense, freshwater forms a lens on the ocean surface. The propagation is determined by local winds and surface currents. From the initial delineation of the plume, we forecast its hourly movement by use of ROMS surface current predictions, see [1]. This prediction is the basis for determining the waypoints of the path. For safety concerns, we restrict a glider to surface no more than once every four hours. Since the basic idea is to track the feature for many days, while assimilating collected data into the model, and the accuracy of the model prediction degrades with time, we choose to plan a 16 hour mission for each day, with $T \in \{0,...,16\}$ denoting the time within a given mission.

The starting location L of each vehicle is known, and we assume that the prediction of the plume evolution is accurate. There is no adaptive behavior incorporated during the execution of the planned path. The idea is to improve the collection of scientific data by predicting the best locations to send a glider, while also providing feedback to JPL on the accuracy of ROMS. In the long run, both communities will benefit. Additionally, we assume that the glider travels at a constant horizontal speed v km/h; d_h km is the distance traveled in h hours.

The input to the centroid-tracking, waypoint-generation algorithm is a set of points, $\mathscr{D}$ (referred to as drifters) that determine the initial extent of the plume ($\mathscr{D}_0$), and hourly predictions ($\mathscr{D}_i, i \in T$) of the location of each point in $\mathscr{D}$. For the points in $\mathscr{D}_i$, we compute the convex hull as the minimum bounding ellipsoid, E_i for $i \in T$. We consider the predicted locations of $\mathscr{D}_0$ after four hours, $\mathscr{D}_4$. The centroid of $\mathscr{D}_4$ is C_4; the centroid of E_4. The algorithm computes $d_g(L,C_4)$, the geographic distance from L to C_4. Given upper and lower bounds d_u and d_l, resp., if $d_l < d_g(L,C_4) \le d_u$, the generated waypoint is C_4, and the path is simply defined as the line $\overline{LC_4}$. If $d_g(L,C_4) \le d_l$, the algorithm first checks to see if there exists a point $p \in E_4 \cup \mathscr{D}_4$ such that

$$d_l \le d_g(L,p) + d_g(C_4,p) \le d_u. \tag{1}$$

If such a point exists, the algorithm generates two waypoints (p and C_4) and the path is defined as the line $\overline{Lp}$ followed by the line $\overline{pC_4}$. If $\{p \in E_4 \cup \mathscr{D}_4 | d_l \le d_g(L,p) + d_g(C_4,p) \le d_u\} = \emptyset$, then the algorithm computes the locus of points, $\mathscr{L} = \{p^* \in \mathscr{L} | d_g(L,p) + d_g(p,C_4) = d_4\}$ and selects a point at random $p^* \in \mathscr{L}$ as another waypoint. Here, the path is the line $\overline{Lp^*}$ followed by the line $\overline{p^*C_4}$. If $d_g(L,C_4) > d_u$, the algorithm generates a waypoint C_w in the direction of C_6, such that $d_g(L,C_w) = d_4$. The location of the vehicle L is updated to C_4 or C_w and the process is iterated until $T \ge 16$. This entire process is presented in Algorithm 1.

Algorithm 1 Centroid-Tracking, Waypoint-Selection Alg.

Require: Hourly forecasts, $\mathscr{D}_i$ for a set of points $\mathscr{D}$ defining the initial plume condition and its movement for a period of time, T.
  for $0 \le i \le T$ **do**
    Compute C_i, the centroid of the minimum bounding ellipsoid E_i of the points $\mathscr{D}_i$. Compute d_4.
  end for
  while $0 \le i \le T-1$ **do**
    if $d_l \le d_g(L,C_{i+4}) \le d_u$ **then**
      The path is $\overline{LC_{i+4}}$.
    else if $d_g(L,C_{i+4}) \le d_l$ and $\exists p \in E_{i+4} \cup \mathscr{D}_{i+4}$ such that $d_l \le d_g(L,p) + d_g(p,C_{i+4}) \le d_u$. **then**
      The path is $\overline{Lp}$ followed by $\overline{pC_{i+4}}$.
    else if $d_g(L,C_{i+4}) \le d_l$ and $\{p \in E_{i+4} \cup \mathscr{D}_{i+4} | d_l \le d_g(L,p) + d_g(p,C_{i+4}) \le d_u\} = \emptyset$. **then**
      Compute $\mathscr{L} = \{p^* \in \mathscr{L} | d_g(L,p) + d_g(p,C_4) = d_4\}$, select a random $p^* \in \mathscr{L}$ and define the path as $\overline{Lp^*}$ followed by $\overline{p^*C_{i+4}}$
    else if $d_g(C_i,C_{i+1}) \ge d_u$ **then**
      Compute C_w such that $d_g(l,C_w) = d_4$ and $AZ(L,C_w) = AZ(L,C_6)^*$.
    end if
  end while

Similarly, we define the boundary-tracking, waypoint-generation algorithm, presented in Algorithm 2. We begin with the same predictions as above, and define P_i to be the polygon formed by connecting the points $\mathscr{D}_i$ for $i \in T$. We define $B(p,r)$ to be the 2-D disc of radius r, about p. This algorithm first computes $N = B(L,d_4) \cap P_4$. If $N \ge 2$, the generated waypoint B_4 is a random selection of one of the intersection points. If $N = 1$, the generated waypoint B_4 is that precise intersection point. If $N = \emptyset$, B_4 is computed such that $d_g(L,B_4) = d_4$ and $AZ(L,B_4)$ is the average azimuth of $\mathscr{D}_i$ for the considered four hour time period. We reassign $L = B_4$, and the algorithm is repeated.

Algorithms 1 and 2 generate the waypoints defining a mission for a vehicle to track an evolving ocean feature. The first version of Alg. 1 was presented in [1]. A preliminary, multi-vehicle simulation result from Alg. 2 is given in [2]. These initial versions of Algs. 1 and 2 were designed to solve the planar path planning problem. Since a glider does not travel on the ocean surface during deployments, and the vertical distribution of velocity cannot be assumed constant, we extend these prior efforts to consider the 3-D path planning scenario including external forcing.

The Ocean Plume Tracking Algorithm BuiLt On Ocean

Model Predictions (OPTA-BLOOM-Pred) takes as input L, the output waypoints Algorithms 1 and 2 (i.e., C_i and B_i for $i = 4, 8, 12, 16$, resp.), as well as the 4-D (three spatial and one temporal) ROMS velocity predictions. The output of the algorithm is an alternate waypoint e.g., C_{4alt} for each input, e.g., C_4. This alternate waypoint is the location to which the vehicle should dead reckon, so that it arrives at C_4, given ROMS predictions of the velocity field during the time the vehicle maneuvers from L to C_4. Figure 2 displays example start, end and dead reckon waypoints for one segment of a mission given by the points labeled Start, Final and Aim, respectively.

Algorithm 2 Boundary-Tracking, Waypoint-Selection Alg.

Require: Hourly forecasts, $\mathscr{D}_i$ for a set of points $\mathscr{D}$ defining the initial plume condition and its movement for a period of time, T.
for $0 \leq i \leq T$ **do**
  Compute P_i, the polygon formed by connecting the points $\mathscr{D}_i$. Compute d_4.
end for
while $i \in \{4, 8, 12, 16\}$ **do**
  $j = i/4$
  if $B(L, d_4) \cap P_i \geq 2$ **then**
    B_j is one of the intersection points chosen at random. $L = B_j$.
  else if $B(L, d_4) \cap P_i = 1$ **then**
    B_j is the precise intersection point. $L = B_j$.
  else if $B(L, d_4) \cap P_i = \emptyset$ **then**
    $B_j = \{p | d(L, B_j) = d_4$, $AZ(L, B_j)$ is the average azimuth of of $\mathscr{D}_i$ for $i = j-4, ..., j\}$. $L = B_j$.
  end if
end while

As previously mentioned, the dynamic equations of motion for an underwater glider have been well-studied and documented (e.g., [18]). Additionally, there are many resources for the kinematic and dynamic equations of motion for underwater vehicles in general (e.g., [25] and [26]). Here, it is noted that the external force arising from ocean currents can be sufficiently approximated by use of the principle of superposition. Thus, the disturbances are considered additive to the dynamic equations of motion as seen in [25]:

$$M\dot{\nu} + C(\nu)\nu + D(\nu)\nu + g(\eta) = \tau + \tau_{current}. \qquad (2)$$

For this study, we do not consider the complete dynamic equations of motion of the vehicle, but initially assume a simple kinematic model, where the total inertial velocity of the vehicle is the sum of the vehicle's body-fixed velocity (relative to motionless fluid) and the inertial velocity of the fluid itself (ocean currents). As an initial assumption, the glider trajectory is parameterized by a cosine curve, containing an integer number of periods (i.e., starts and ends at the surface), that is estimated from data collected over the course of multiple field deployments. Note that OPTA-BLOOM-Pred can accept any time-discretized, periodic vehicle trajectory. The glider's velocity along this parameterized trajectory is estimated from a glider simulator provided by the vehicle manufacturer, then normalized so that the average

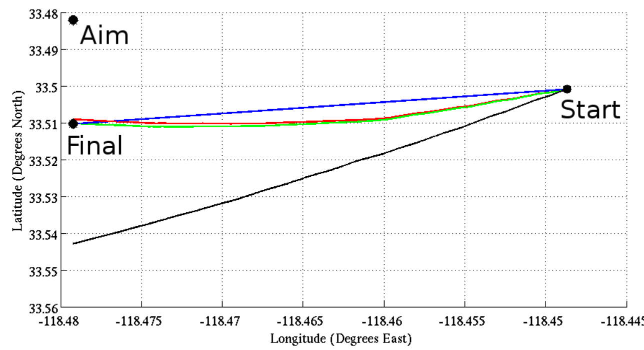

Fig. 2. Iterative algorithm output to determine the bearing and range at which the vehicle should dead reckon. The blue line is the initial path if no ocean current existed. The black line is the first iteration attempt. The point labeled Aim is the dead reckoning waypoint at which the vehicle heads to end up at the point Final, following the green line.

horizontal speed is v km/h. Based upon favorable proof-of-concept deployment results utilizing these algorithms, work is ongoing to incorporate the dynamic equations of motion to produce vehicle trajectories.

Given the inputs above and starting locations L_C and L_B for the gliders, OPTA-BLOOM-Pred computes a sinusoidal trajectory from L_C to C_4. When projected to the sea surface, this initial path minimizes the Euclidean distance between L_C to C_4. Based on the assumed speed of the glider, an estimated completion time $\mathbb{T}$ is computed. This trajectory, $P(x, y, z, t)$, is discretized into 30 s time steps ($\mathscr{T}$) and the predicted current is superimposed iteratively at each step. To incorporate the current, we use a fixed-step integrator along the trajectory. At each time step t_j, $j \in \mathscr{T}$, we add the velocity component vectors of the vehicle and predicted current, and compute the resultant displacement for the duration t_j. The predicted current is the average value of the eight nearest grid points defining the cube containing ($P(x_j, y_j, z_j, t_j)$). Then, OPTA-BLOOM-Pred computes $e = d_g(P(x_\mathbb{T}, y_\mathbb{T}, z_\mathbb{T}, t_\mathbb{T}), C_4)$. If $e <$ 100 m, $C_{4alt} = C_4$. Otherwise, we compute the northing (N_{err}) and easting (E_{err}) errors between $P(x_\mathbb{T}, y_\mathbb{T}, z_\mathbb{T}, t_\mathbb{T})$ and C_4. We take $C_{4alt} = P(x_\mathbb{T} + k * E_{err}, y_\mathbb{T} + k * N_{err}, z_\mathbb{T}, t_\mathbb{T})$[¶], and iterate the above procedure for the trajectory starting at L_C and ending at C_{4alt}. The result is $C_{4alt} \neq C_4$ such that, under the predicted conditions, the vehicle is predicted to surface within 100 m of C_4. An example output of the iterative path planning process is presented in Fig. 2.

Tracking a dynamically evolving feature is highly time-dependent. Reaching a specified location has an associated, or accepted time of arrival. For a glider, time is lost at the surface due to GPS localization and communication. Thus, in addition to safety, it is in our best interest to minimize surfacings. To this end, in the computation of the centroid tracking waypoints, we additionally consider predicted feature centroids at 5, 6, 7 and 8 hours from L_C. The same iterations are applied, and a time to goal is estimated for C_{Jalt}, $J = 5, 6, 7, 8$. The waypoint with the path that has an estimated end time closest to the time the centroid will be in that predicted location is chosen as the waypoint at

[¶]Here, $0.5 < k < 0.9$ is a weighting parameter controlling the rate of convergence of the iteration.

which to surface. Note that this procedure may reduce the total number of surfacings over the duration of the mission.

For the boundary tracking mission, we implement the same iterations to compute B_{Jalt}, $J = 4, 8, 12, 16$. However, we do not consider the optimization described in the previous paragraph. As the boundary is not a single point location, it is not as critical to match its precise spatial and temporal location. Additionally, we expect the prediction of the boundary of the feature to be less accurate since it is predicted by the evolution of an unconnected, discrete number of points.

This process produces 4 boundary waypoints, and at most 4 centroid waypoints. The overall OPTA-BLOOM-Pred is given in Algorithm 3. A simulation result of the implementation of this collection of algorithms is given in Section IV. We follow the simulation with field tests to validate the current integration procedure and the computation of the alternate waypoints.

Algorithm 3 Ocean Plume Tracking Algorithm BuiLt On Ocean Model Predictions (OPTA-BLOOM-Pred)

Require: A significant fresh water plume is detected via direct observation or remotely sensed data.
- **repeat**
  - A set of points ($\mathscr{D}$) is chosen which determine the current extent of the plume.
  - Input $\mathscr{D}$ to ROMS.
  - ROMS produces an hourly forecast for all points in $\mathscr{D}$.
  - Input hourly forecast for $\mathscr{D}$ into Algs 1 and 2.
  - Execute waypoint generation, Algs. 1 and 2.
  - Execute algorithm on centroid waypoints to coordinate spatial and temporal movement of the feature.
  - Compute the alternate waypoints at which the vehicle aims, to arrive at the prescribed goal location.
  - Uploaded computed alternate waypoints to the AUV.
  - AUV executes mission.
  - The AUV sends collected data to ROMS for assimilation into the model.
- **until** Plume dissipates, travels out of range or is no longer of interest.

IV. Simulation

Here we present a simulation result for the implementation of OPTA-BLOOM-Pred. In this example, a proxy feature of interest is delineated off the coast of Newport Beach, CA to emulate a fresh water plume. In Fig. 3, we present the results of a 16 hour feature tracking mission. Figure 3A shows an overview of the area where the proxy feature was delineated. Figures 3B-F present the proposed mission in 4-hour time increments. The starting location for both gliders is given by the black star. Boundary tracking waypoints are given by red triangles, centroid tracking waypoints are given by yellow diamonds, the centroid of the current state of the plume is given by the orange dot, and the green dots represent the alternate waypoint at which the gliders dead reckon. In Fig. 3E, the path tracking the centroid remains the same as that presented in Fig. 3D. Here, OPTA-BLOOM-Pred computed that it was better to surface after eight hours rather than after four hours. Although the glider did not start directly at the centroid, by hour eight, it is supposed to surface directly at its predicted location. This occurs again at $T = 16$. We remark that in Figs. 3D-F, it appears that the computed centroid does not appear to be in a centralized location. This is a result of computing the centroid based on the convex hull of the set of drifters. Since the boundary of this feature evolves into a non-convex shape, the centroid migrates toward the concave boundary.

It is interesting to note that neither of these paths would be defined by a human operator, and at first glance, are seemingly somewhat random. However, they are designed to track an evolving feature that does not move following set patterns. This tracking appears to work well and gives promise to the implementation of trajectories generated by model predictions. In each of Figs. 3B-F, we can see that the difference between dead reckoning location and goal location can be vastly different based on location and time. The alternate waypoints at which to dead reckon heavily depend on the accuracy of ROMS. The field trials presented in the following section provide an initial investigation into the accuracy of ROMS and the validity of this method of technology fusion.

V. Field Experiments

As previously mentioned, ROMS assimilates ocean surface current data from HF radar stations. At this time, there are no permanent instruments providing subsurface velocity measurements. Thus, one may assume that the validity of ROMS predictions would decrease with depth, especially with the diverse bathymetry present in a coastal regions. In this section, we refer to the distance between the actual surfacing location and the prescribed surfacing location as the surfacing error.

To warrant further investigation into the federation of ROMS predictions and AUV simulations for trajectory and path planning, we present some preliminary field experiments. As a proof-of-concept of merging existing technologies to create a novel toolchain for feature tracking, we do not initially implement a full-scale mission as seen in Section IV. Instead, we consider multiple, single-segments for two scenarios; a deep mission (max depth of 80 m) and a shallow mission (max depth of 10 m). An example segment for a deep mission is given in Fig. 4.

A Slocum glider has an internal, low-level controller that computes a dead reckoning range and bearing from its current position to the next waypoint. By comparing its actual surfacing location to the prescribed goal location, the glider computes an average current velocity and direction during its previous mission segment. This computation is used to determine the dead reckoning waypoint. The details of this computation and low-level controller are a black-box.

To investigate the practical applicability of our methods, we first examined data from prior deployments. In April and May 2009, we conducted a month-long, two glider deployment (details in [4] and [5]). During this time the two gliders collectively traversed nearly 1000 km of ocean and surfaced more than 200 times due to the arrival at

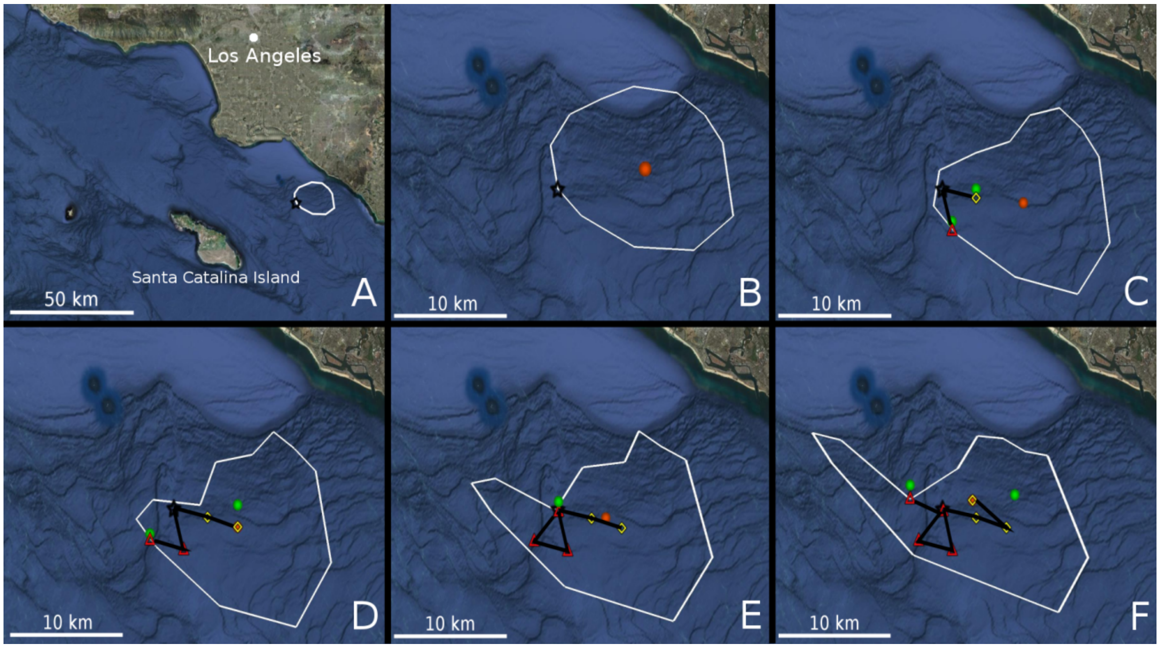

Fig. 3. OPTA-BLOOM-Pred simulation results. Tracking of a proxy feature for 16 hours off the coast of Newport Beach, Los Angeles, CA. Images created by use of Google Earth.

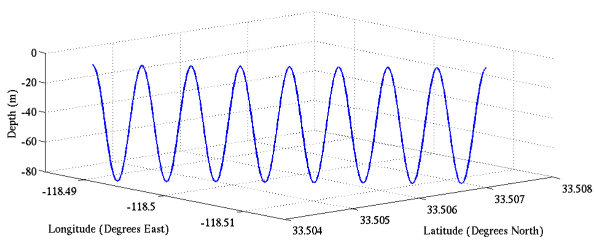

Fig. 4. Simulated glider segment for an 80 m mission.

a prescribed waypoint. Based on the primary objective to collect communications data (i.e., surface frequently), the average distance between waypoints was slightly greater than 2 km. Over this collection of surfacings, the median surfacing error was 1.1 km. In August 2009, we deployed a single glider on a similar mission. Considering 23 surfacings, with waypoints an average of 1.4 km apart, the median surfacing error was 0.8 km. The combined data from these deployments suggests a potential to improve the accuracy of glider navigation by coupling ROMS predictions with glider simulations.

To investigate this possibility, we utilized ROMS predictions as presented above to compute the dead reckoning location instead of using the on-board controller. First, we acquired the vehicle's position when it surfaced, P. A random waypoint E (ending location) is chosen between 1 and 3 km from P. Using the up-to-date ROMS prediction for the given time, we implemented the iterative velocity integration described in Section III to determine the dead reckoning waypoint. The dead reckoning waypoint is uploaded to the glider, and the mission is executed. From the time the glider surfaces, it takes roughly 10 minutes before it is sent off again. To reduce the number of variables, we conducted the deep and shallow missions 24 hours apart, to use the same temporal portion of the ROMS prediction. Additionally, velocity calculation parameters stored on-board the vehicle were set to zero before each segment; our modifications were the only compensation used by the vehicle. To determine the improvement we could gain by use of ROMS, we present the results from 10 experimental trials.

For the deep missions, the average segment length was 1.7 km, and the mean and median surfacing error was 0.5 km. For the shallow missions, the average segment length was 1.5 km, and the mean and median surfacing error was 0.7 km. In both scenarios, we observe a reduction in surfacing error, implying there is some accuracy to be gained by incorporating ROMS predictions into AUV path planning. It is interesting to note that, contrary to our assumption that ROMS accuracy decreases with depth, the deep missions exhibit a larger reduction in surfacing error. This is an area of active investigation.

VI. Conclusions and Future Work

Since the waypoint selection algorithms and simulation result for OPTA-BLOOM-Pred presented here are extensions of work published in [1] and [2], we focus this discussion on the field deployment results. These results are critical to realizing the end goal of implementing and iterating OPTA-BLOOM-Pred to track an evolving ocean feature.

Typical current velocities in the SCB are not only large in magnitude, but may also be a component of a complex structure, such as an eddy. Such conditions increase the difficulty in both modeling the region and implementing missions. This is evident from an average surfacing error of ~ 1 km during two month-long deployments.

Incorporation of ROMS predictions into our path planning procedure slightly reduced our observed surfacing error. However, these improvements provide motivation to further investigate the innovative toolchain presented here. At this juncture, we are not able to, nor do we expect to, *fine tune* navigation to meter-level accuracy, but we envision that through continued collaboration between the ocean modeling and AUV communities, high precision can be achieved. We remark that although the number of experimental trials completed is relatively small, this is not a direct implication to the level of effort involved in obtaining the data. As previously mentioned, we have gathered enough data through many past deployments to be confident that the preliminary results presented here warrant further investigation.

With this being an initial investigation of the fusion between a large-scale, high-resolution ocean model and a glider simulation, there are many areas on which to improve. First, we plan to conduct more field trials to further validate and assess the ROMS velocity predictions. These trials will be conducted at different times to investigate the full temporal regime of ROMS. Secondly, we plan to examine alternate input trajectories to the algorithm to test this component. Lastly, this research is a small portion of a large effort that is preparing a region-wide, coastal-ocean survey called *Bight 2010*. This is a multi-facility, comprehensive study of the SCB. *Bight 2010* is planned for January 2010 through March 2010, and we are planning to implement OPTA-BLOOM-Pred with four AUVs to track and monitor an actual fresh water plume or algal bloom.

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