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Station Keeping with an Autonomous Underwater Glider Using a Predictive Model of Ocean Currents

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Abstract

We investigate the use of an autonomous underwater glider as a platform for a virtual mooring. Our approach uses a simple vehicle motion model, a predictive model of ocean currents, and a greedy search algorithm in order to simulate possible actions available to the vehicle and select an action to minimize the distance from the target point. Results from a 19 day experiment in October 2016 near Monterey Bay are presented where we test our control algorithm as well as investigate the effect of a glider's dive profile on its ability to act as a virtual mooring.

Introduction

Surface Water and Ocean Topography (SWOT) is a future NASA mission, set to launch in 2021, aimed at better understanding Earth's oceans and terrestrial surface water [Jet Propulsion Laboratory]. A vital aspect of the mission involves calibrating and validating sensors using in situ measurements. In order to do this, moorings are required at specific locations in the over flight path of the satellite. Deploying physical moorings at all the required locations would be expensive and time consuming.

As an alternative to this approach, a dynamically controlled marine vehicle can be used as a virtual mooring. Marine vehicles are simpler and cheaper to deploy, and more flexible once deployed. Multiple vehicles can be deployed at a single, easily accessible location, then commanded to a final position for the virtual mooring. During a deployment, the virtual moorings can be moved with ease, quickly responding to changing priorities. When the deployment is completed, the vehicles can be commanded to rendezvous at a single location to facilitate recovery.

In order to act as a virtual mooring, a vehicle must be able to station keep at a given position. There are any number of vehicles with varying costs and capabilities to consider for this task . These range from inexpensive vertically profiling floats with no horizontal control and deployment times on the order of years, to more expensive short range AUVs with significant control authority – at approximately 2.5m/s horizontally – and deployment times on the order of hours. [OceanServer ; Woods Hole Oceanographic Institution].

Underwater autonomous gliders are a promising choice for a virtual mooring, as they are inexpensive compared to a physical mooring, capable of being deployed for months at a time, and can travel horizontally at approximately 0.25 m/s. [Hodges and Fratantoni 2009] and [Rudnick, Johnston, and Sherman 2013] both used gliders as virtual moorings with some success. [Hodges and Fratantoni 2009] achieved an average distance from the mooring location of 2.0 km and [Rudnick, Johnston, and Sherman 2013] achieved an average distance of 3.6 km and 1.8 km in two separate experiments.

Our approach to station keeping uses a greedy search algorithm and a predictive model of ocean currents in order to simulate the vehicles motion and select the control action that results in the best station keeping performance.

The remainder of the paper is organized as follows. First we discuss the problem we are trying to solve and our proposed solution. Then, we present the results from our experiment in October 2016. Finally, we discuss the next steps in order to further improve and validate our method.

Problem Definition

This experiment investigates the problem of station keeping with a autonomous underwater glider. Our approach requires a simple motion model for the vehicle, a predictive model of ocean currents as inputs, as well as a target location. The goal is to minimize the average station keeping error, where error is the distance between the glider position and the target station keeping location.

Path Planner

We employ a continuous, greedy planning algorithm to generate the required control sequences. On each surfacing the glider sends an updated location to the shore based planner, which then generates a control sequence based on this new location. The updated control sequence is then sent to the glider. All of this occurs on one surfacing, allowing for closed loop control. Our planner conservatively requires 15 seconds to generate a plan from when the glider first connects to the shore based control workstation, which includes retrieving the vehicle location and loading the required model data. The glider is nominally on the surface for 10 to 15 minutes total, depending on the amount of data it is sending to shore and the quality of the satellite data link. This control path is show in Figure 1

Three parameters are used to define each dive: glide slope, depth, and heading. The planner assumes a fixed glide

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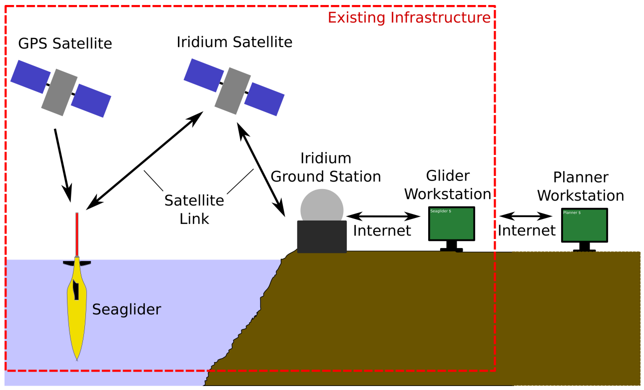

Figure 1: Control path used to command the Seaglider.

slope and depth. The heading is determined by discretizing the continuous search space into a set of possible actions. A single dive is simulated for N headings equally spaced over some search angle. The search angle is centered toward the target surfacing location of the glider. In this case, the target surfacing location is the target station keeping location. After the N dives are simulated, the heading that results in the minimum distance between the simulated surfacing location and the target surfacing location is converted into a waypoint and sent to the glider. Note that this is exhaustive search of the discretized search space. Figure 2 shows this process. For our experiment we used a search angle of 60° and simulated 15 headings. This approach can be viewed as optimal for a search depth of one with the given set of actions.

In order to simulate the glider, a simple vehicle motion model and ocean model with predictive currents are required. A fixed glide slope, speed, and dive depth are defined for the vehicle. The simulated glider dives at this fixed glide slope and speed to the fixed depth. At specified time intervals the currents affecting the glider are updated based on the ocean model and the latitude, longitude, depth, and time of the glider. The ROMS current velocity is linearly interpolated in 4 dimensions and added to the horizontal velocity calculated from the speed, glide slope, and heading. This results in the final velocity of the glider at a given time.

Experiment

From October 1st 2016 to October 19th 2016 we performed a station keeping experiment near Monterey Bay. The location of the virtual mooring was (36.578°N,122.226°W), shown in Figure 3. The vehicle used in the experiment was a Seaglider [Eriksen et al. 2001]. The vehicle speed used in the planner simulation was empirically determined from dives at the start of the deployment, before the station keeping experiment began. During the experiment, the planner did not control the glide slope and depth of the glider, only the heading. Instead, the glide slope and depth were manually modified to test the effect on the vehicle. By varying these two parameters, we are able to modify the horizontal distance traveled per dive. As the glider cannot change direction during a dive, decreasing the horizontal distance traveled per dive should reduce the station keeping error.

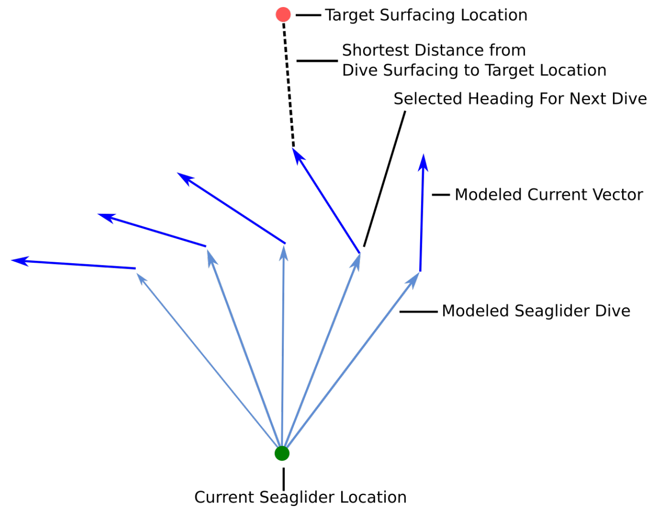

Figure 2: Visualization of the path planning algorithm, showing the glider movement and current vector for the simulation of each possible heading.

Ocean Model

Our approach requires an ocean model with predictive currents at multiple depths and a sufficient timespan. Some widely used ocean models that fit this criteria include the Regional Ocean Modeling System (ROMS) [Chao et al. 2009], the Harvard Ocean Prediction System (HOPS) [Robinson 1997], the Princeton Ocean Model (POM) [Mellor 1998], and the Hybrid Coordinate Ocean Model (HYCOM) [Chassignet et al. 2007].

We used the Regional Ocean Modeling System (ROMS). The grid spacing in the ROMS model was approximately 300m x 300m, with 24 depths ranging from 0m to 1200m with non-uniform spacing. Each model consisted of 48 time slices at 1 hour intervals. A new model was available every 24 hours, incorporating the most recent observed data. The list of inputs used in the ROMS model can be found in [Troesch et al. 2016b]

Results

Figure 4 shows the position of the glider at each surfacing. The colored points represent different values for the glide slope and dive depth. Figure 5 shows the estimated probability density function of the vehicle locations for each set of parameters. Unless specified, the dive depth is 1000m. It is important to note that while the probability density functions are useful, the surfacing position of each dive is not independent from the position of previous dives. From the calculated probability density functions, we can see that as the horizontal distance traveled per dive is decreased – achieved by increasing the glide slope or decreasing the dive depth – the average error and variance decrease. Presumably this would break down at some point as the vehicle would no longer be able to counteract the currents driving it away from the target location. A shallow dive depth would also result in the glider remaining in the upper layer of the ocean with

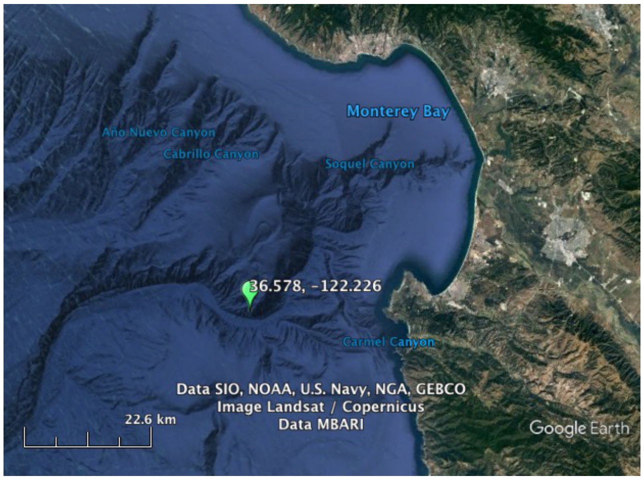

Figure 3: Location of October 2016 station keeping experiment near Monterey Bay

stronger currents.

In order for a virtual mooring to be used by the SWOT mission to calibrate and validate sensors on-board the satellite. [Wang et al. 2017] is producing an estimated PDF from a glider simulation and comparing it to the estimated PDF from this experiment in order to determine the validity of their simulation.

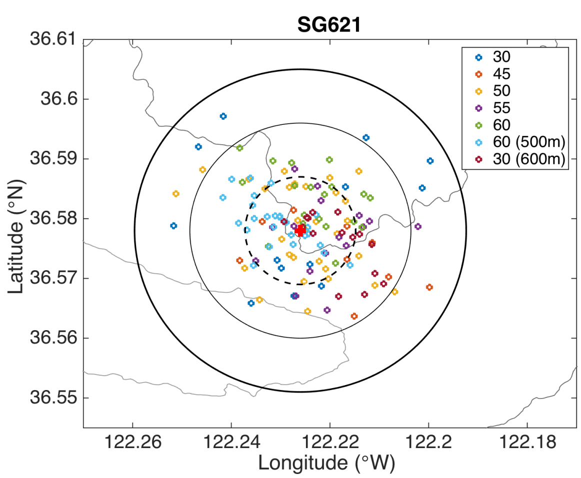

Figure 4: Surfacing positions of the glider for varying glide slopes (degrees) and dive depths (meters). The plotted range circles are at 1 km, 2 km, and 3 km from the target station keeping location. Unless otherwise stated the max depth is 1000m

Related Work

Some work has been done regarding station keeping with marine vehicles. [Hodges and Fratantoni 2009] and [Rudnick, Johnston, and Sherman 2013] both use gliders as virtual moorings, however, they do not use an ocean current model to generate control sequences. [Troesch et al. 2016b] presents an approach for station keeping with floats also using ROMS. [Troesch et al. 2016a] investigates model accuracy and batch versus continuous planning in the context of station keeping. There has been work done with general path planning of underactuated marine vehicles. [Thompson et al. 2010] uses the ROMS model with wave-front propagation in order to control gliders. [Eriksen et al. 2001] uses rapidly exploring random trees in order to plan glider paths over long distances. [Pereira et al. 2013] uses path planning in order to prevent gliders from surfacing in dangerous locations. [Dahl et al. 2011] uses a number of planning algorithms in order to optimize float coverage across all oceans. [Alvarez, Garau, and Caiti 2007] uses a genetic algorithm with no ocean model in order to control a network of floats and gliders.

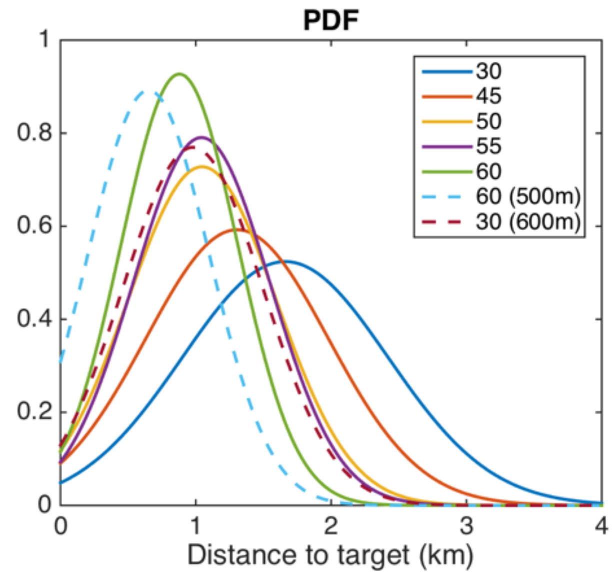

Figure 5: Probability Density Function of glider station keeping with varying glide slopes (degrees) and dive depths (meters). Unless otherwise stated the max depth is 1000m

Future Work

We are interested in further investigating the use of a non-greedy search strategy. We do not expect this to provide much benefit with our current approach because the predictive accuracy of the model decreases as time progresses, uncommon currents would likely be necessary to result in an improved plan over the greedy search, and we are able to re-plan at each surfacing. However, a non-greedy search strategy could prove beneficial when used with a Slocum glider.

Slocum gliders are able to fly to multiple waypoints per dive by using dead reckoning. This has the potential to improve station keeping as it removes the limitation that requires a glider to maintain a heading for one full dive. A current-aware algorithm would be able to select waypoints in order to compensate for drift during the dive. A non-greedy search strategy could be beneficial in this case because it would operate over a single dive in order to use only the most accurate part of the model, actions earlier in a dive could be sub-optimal as currents can vary significantly with depth, and re-planning is not possible mid-dive. The search space of a non-greedy algorithm would be large enough to exclude the possibility of exhaustive search; an approach such as rapidly-exploring random trees or best-first search would be required.

Slocum gliders are also able to use a hybrid attachment to periodically increase the speed of the glider at the cost of energy [Jones, Allsup, and DeCollibus 2014]. The planner would need to incorporate information past a single dive to optimally use the thruster and insure that the glider conserves enough energy to remain deployed for the required time.

Our current strategy could be improved by allowing the planner to dynamically vary the dive profile of the vehicle through modifying the glide slope and dive depth, as well as adding alternative dive patterns, such as helix dives, to the possible set of actions. This would allow the behavior to be further modified depending on the vehicles position and ocean current conditions. For example, when the vehicle is in a high current area, deeper dives can be used in order to take advantage of the lower currents at depth. Having a more complete set of possible actions can only be beneficial as the planner will still chose the action that results in the minimal error. A model sensitivity analysis would provide a better understanding of how this approach performs with degrading quality of the ocean current model. Finally, more deployment time will allow further verification of this approach to station keeping. We currently have a deployment scheduled for June 2017.

Conclusion

The glider was able to achieve an average error of under 1 km during this experiment. In addition to this, we showed that the glide slope and dive depth can be varied to improve station keeping. Steeper glide slopes and shallower dive depths reduce the horizontal distance traveled by the glider in a single dive, thus allowing for finer control over the position of the glider and a reduction in the average error. However, using shallower depths has the trade-off of forgoing the data at deeper depths in order to maintain a position that is closer to the target location.

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