Ocean Flow Predictions for Autonomous Underwater Vehicle Navigation: Tradespace Between Vehicle Navigation Performance and Ocean Model Accuracy (DRAFT)

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ABSTRACT (Body text, Times New Roman, 12 pt, bold)

The motions of autonomous underwater vehicles (AUVs), especially slow-moving vehicles, are perturbed by ocean flow. To account for the influence of flow, knowledge of ocean flow is incorporated in planning vehicle trajectories. An important source of knowledge of flow is ocean models. Surrogate is a data-driven ocean model whose model parameters are trained using historic ocean flow data. Surrogate has been validated using HF-radar data collected from the California coast of the United States. During January to April 2012, two gliders were deployed off the coast of Long Bay, South Carolina to investigate a mechanism that drives the formation of persistent wintertime phytoplankton blooms. The ocean in the survey area is characterized by strong tidal and Gulf stream currents, and to navigate the gliders, a hybrid ocean current model was developed to provide flow predictions in the vicinity of gliders. Motivated by the Long Bay deployment, in this paper, Surrogate is used to model ocean flow off the coast of Georgia. In general, higher ocean model accuracy requires higher computing

power and time. To balance AUV navigation performance and overhead associated with ocean model accuracy, we propose a metric called tradespace.

INTRODUCTION

An autonomous underwater vehicle (AUV) is an oceanic sensing platform that operates with minimal human input. Its navigation is mostly performed based on waypoints, which accounts for the navigation paths. In addition, the ocean currents have significant influence on the navigation paths, so they should be taken into account in the path planning.

Ocean currents prediction methods are largely classified into empirical models and physics-based models. Physics-based models take into account recent observations to capture the unexpected ocean dynamics that is not accounted for in the models. However, this data assimilation usually takes a while due to the huge data processing. Thus, in a region where the ocean dynamics is highly variable, the physics-based models might not be able to provide AUVs with timely information for path planning. In this paper, we present an application of an empirical model to provide underwater gliders flying under strong currents with ocean currents predictions.

Regardless of what type of ocean models, we have to deal with the currents prediction errors. In making efforts to improve ocean currents predictions, it has been an issue how much increase of the vehicle navigation performance is anticipated from the efforts. In this paper, we present how to evaluate the navigation performance given the prediction error to maximize the cost-effectiveness between them.

MOTIVATION

In my last field experiment conducted to study persistent wintertime phytoplankton blooms in Long Bay, SC, two gliders were deployed. The gliders were controlled using waypoints, and the waypoints were generated by computing predicted glider trajectories based on ocean currents predictions. Compared to HF radar observations, existing operational physics-based ocean forecast models did not provide good data quality enough for glider path planning in an area that is often affected by Gulf Stream. Thus, we are trying to use an empirical model that uses historic HF radar data for the following field experiment.

METHODS

Two existing physics-based operational ocean models are tested for glider navigation in the field experiment in Long Bay, SC in 2012. However, they were not appropriate to use for glider path planning because the error between their ocean currents forecast and HF radar observation sometimes exceeds glider's horizontal speed. Surrogate (S. Frolov et al.) is an empirical model that trains a prediction model using historic HF radar data and is proven to be better than some of the existing physicsbased ocean models for the West coast.

SURROGATE

Surrogate first analyzes EOFs of the data to reduce the dimension of the system. Figure 1 shows the first EOF, and we can see that the first EOF excludes Gulf Stream components out of the data and takes the major tidal components.

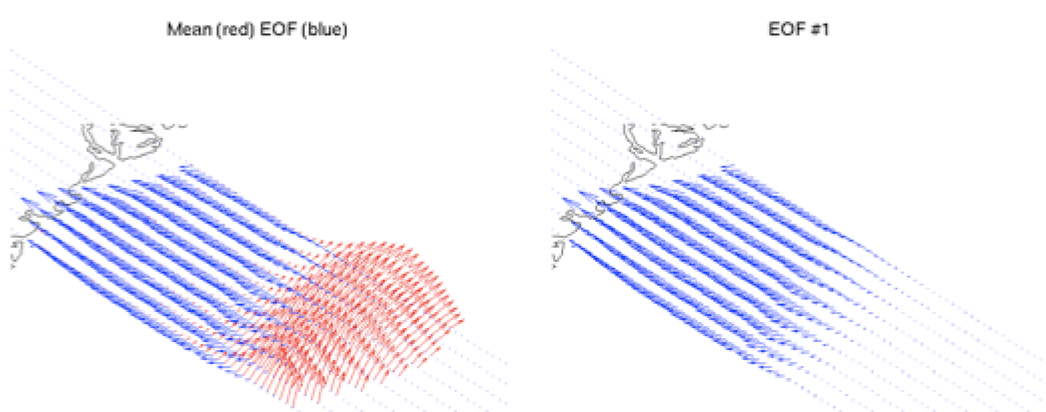


Figure 1. The first EOF.

Figure 2 shows how well EOFs capture the energy of the ocean dynamics in the domain. By using up to the first 20 EOF functions, we can capture 80% of the energy.

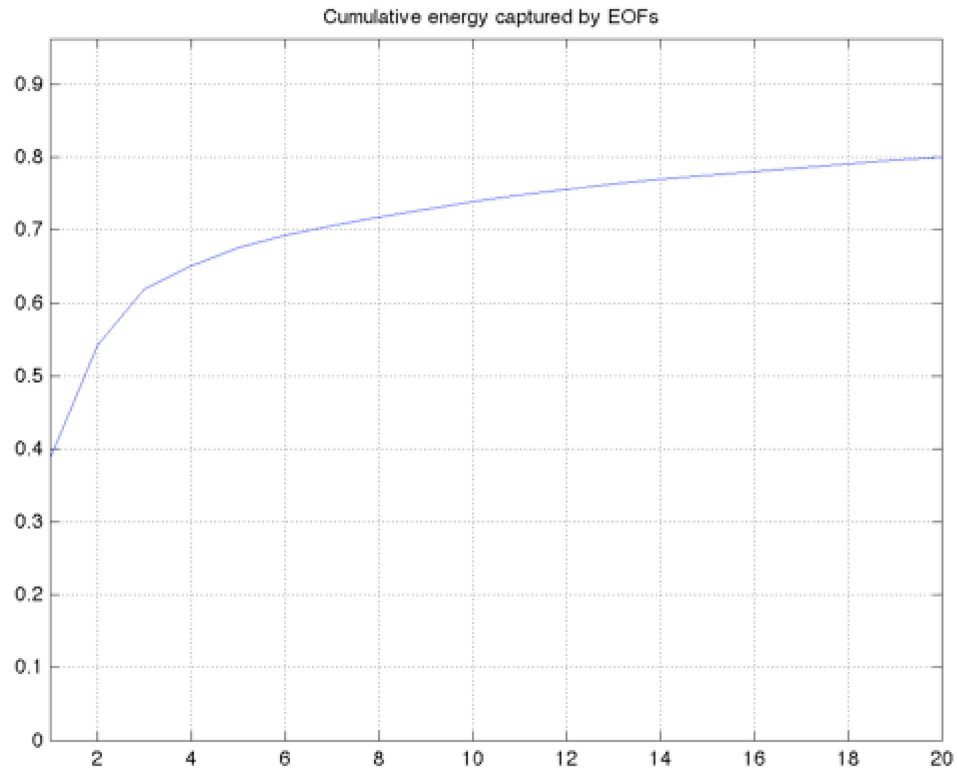
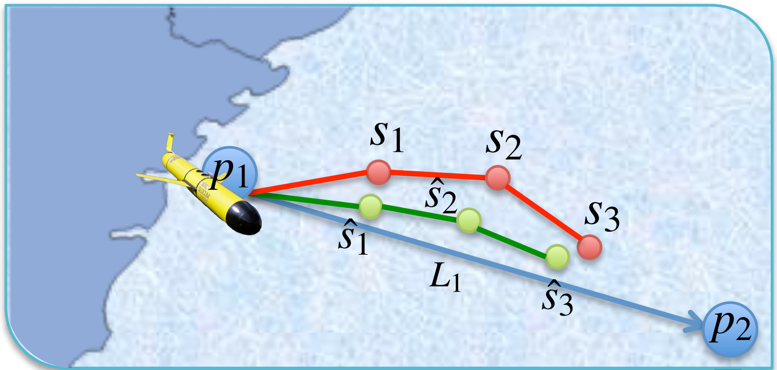


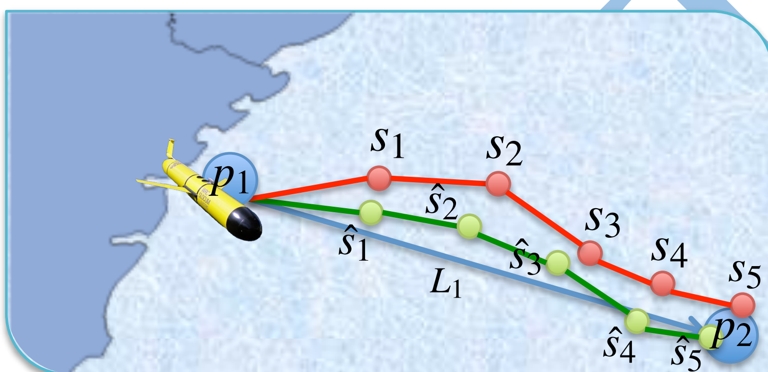
Figure 2. Energy captured by EOFs

METRICS FOR VEHICLE NAVIGATION PERFORMANCE

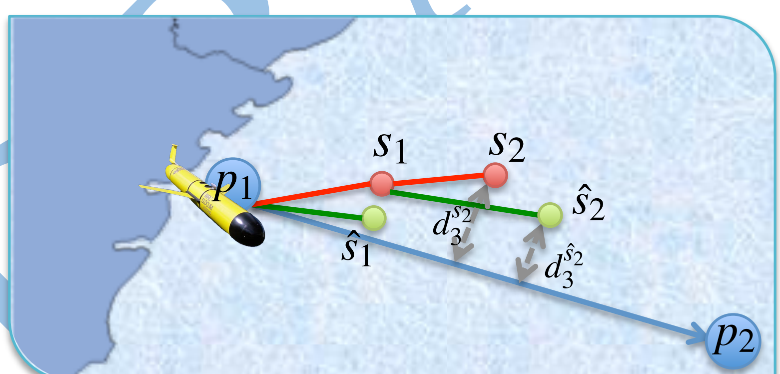
To evaluate AUV navigation performance, five vehicle navigation performance metrics as in Fig. 3 are designed. The metrics are designed for waypoint-based navigation missions and return performance error in various aspects of vehicle navigation. Suppose we have a vehicle whose surfacing interval is h hours, and we have two target positions p_1 and p_2 for the vehicle. A transect mission is to travel between p_1 and p_2 back and forth, and a virtual mooring mission is to maintain its station at p_1. The metrics shows error propagation as the mission keeps repeating.



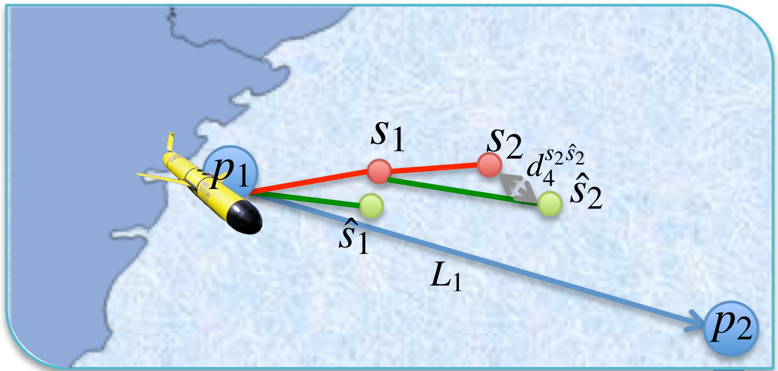
(a) Error in vehicle speed



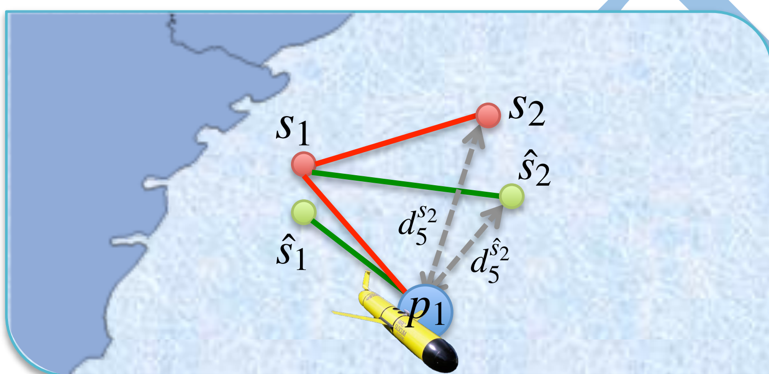
(b) Error in vehicle velocity



(c) Error in closeness to the transect



(d) Error in surfacing position



(e) Error in virtual mooring

Figure 3. Vehicle navigation performance metrics. Each of them provides performance error in various aspects of vehicle navigation

There are various navigation algorithms, and the performance of AUV navigation would vary depending on the navigation algorithms. defined for each algorithm to measure the performance specific for a AUV mission. In this report, we define a general pattern that can be used to measure the AUV navigation performance. The metric in Fig. 3(a) represents error in vehicle speed and is computed as

$$J_1 = \frac{\sum_i \{s_i - s_{i-1}\}}{\gamma} - \frac{\sum_i \{\hat{s}_i - \hat{s}_{i-1}\}}{\gamma},$$

where s_i and $\hat{s}_i$ are ith surfacing and predicted surfacing, respectively, and γ is given time. Figure 3(b) describes error in vehicle velocity computed as

$$J_2 = \frac{l}{t_f - t_0} - \frac{l}{\hat{t}_f - t_0},$$

where l is the length of the transect line, t_0 is the mission start time, t_f is the mission completion time, and $\hat{t}_f$ is the predicted mission completion time. Figures 3(c) and 3(d) are errors in closeness to the transect and in surfacing position, respectively, such that

$$J_3 = \frac{1}{n} \sum_{i=1}^{n} \left\{ \frac{d_3^{s_i} - d_3^{\hat{s}_i}}{h} \right\}$$

$$J_4 = \frac{1}{n} \sum_{i=1}^{n} \left\{ \frac{d_4^{s_i \hat{s}_i}}{h} \right\},$$

where n is the number of surfacings, $d_3^{s_i}$ and $d_3^{\hat{s}_i}$ are the distances from ith surfacing and predicted surfacing to the transect line, respectively, and $d_4^{s_i \hat{s}_i}$ are the distance between ith actual and predicted surfacings. The last metric in Fig. 3(e) is error in virtual mooring defined as

$$J_5 = \frac{1}{n} \sum_{i=1}^{n} \left\{ \frac{d_5^{s_i} - d_5^{\hat{s}_i}}{h} \right\},$$

where $d_5^{s_i}$ and $d_5^{\hat{s}_i}$ are the distances from ith actual and predicted surfacings to the virtual mooring position, respectively. The last three metrics account for the error between the actual surfacing position and the predicted surfacing position.

TRADESPACE

Incorporating ocean currents prediction into AUV path planning will enable optimal path planning, but it would not be perfect due to prediction error. The prediction may be able to improve, but we need to quantify how the decrease of the prediction error relates to the navigation performance improvement. To evaluate vehicle navigation performance given currents prediction errors, we propose a tradespace between the vehicle navigation performance error and the currents prediction error as in Fig. 5. The idea is that we would like to set up a performance error threshold that maximizes cost-effectiveness between the vehicle navigation performance error and the currents prediction error.

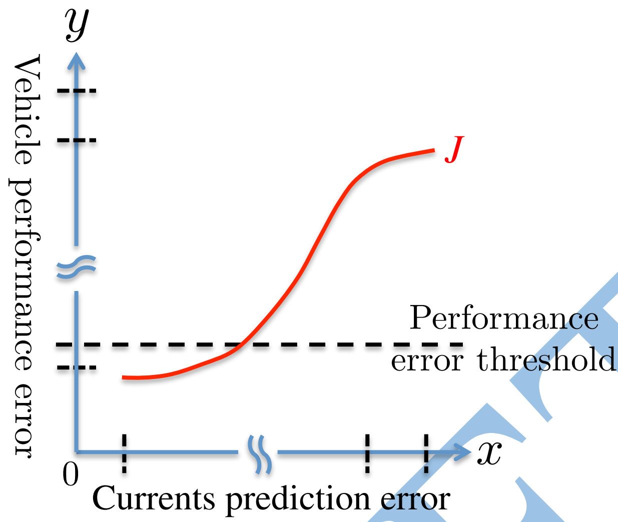


Figure 4. Tradespace for navigation performance associated with ocean model accuracy

Suppose we have a predicted flow field $\mathbf{f}_p$ and a real-time observed flow field $\mathbf{f}_o$. The prediction error is defined as the residual between the two vector fields such that

$$\mathbf{r}_f = \mathbf{f}_p - \mathbf{f}_o.$$

The idea is that we want to improve the ocean prediction model towards the real-time measurement. Let us define test prediction such that

$$\mathbf{f}_{test} = \mathbf{f}_o + \alpha \mathbf{r}_f,$$

where $\alpha = [0, 1]$. When $\alpha = 1$, $\mathbf{f}_{test}$ is equal to the original predicted flow field. As $\alpha \to 0$, $\mathbf{f}_{test}$ becomes close to the real-time measurement. Then, we denote by x root mean square error between $\mathbf{f}_o$ and $\mathbf{f}_{test}$ such that

$$x = \left\| \frac{1}{ml} (\mathbf{f}_o - \mathbf{f}_{test}) \right\|_2,$$

where $\|\cdot\|_2$ is L^2 norm, m is the number of spatial samples, and l is the number of time samples.

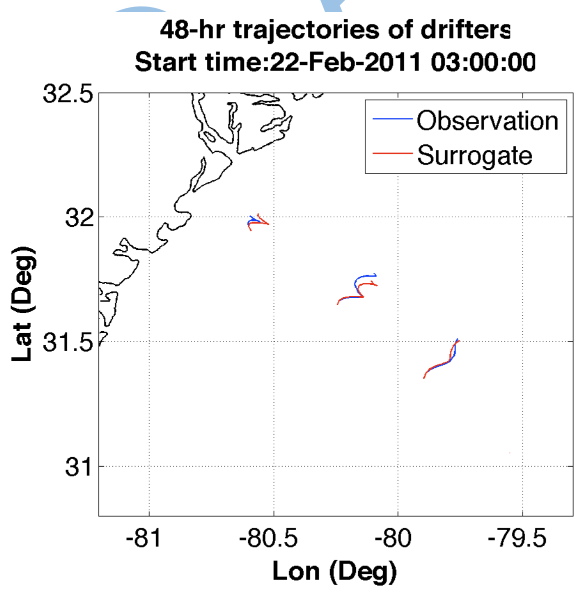
We have defined five vehicle navigation performance metrics. The metrics will be measured using $\mathbf{f}_o$ and $\mathbf{f}_{test}$. Let $J = [J1, J2, J3, J4, J5]^T$ and $\mathbf{W}$ be a diagonal matrix with w_i, $i = \{1, \cdots, 5\}$, which is a relative weight to each of the performance metric. We define the navigation performance error y as

$$y = \frac{1}{tr(W)} J^T W J$$

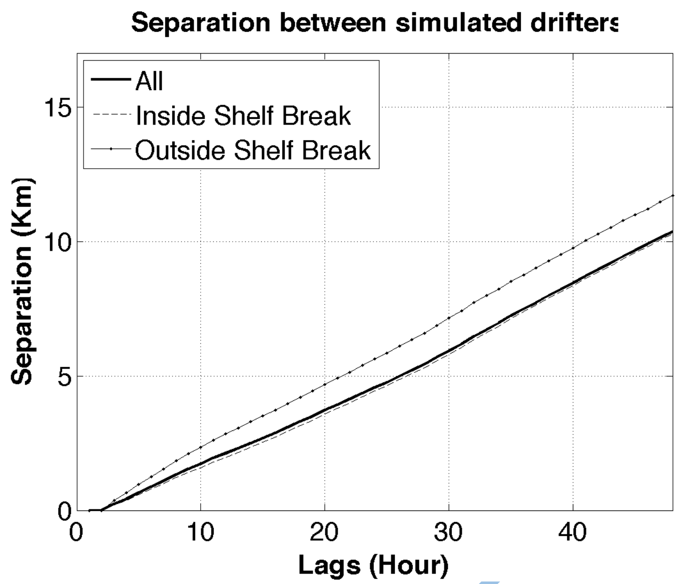
RESULTS (Normal, Times New Roman, 12 pt, bold)

SURROGATE VALIDATION

The prediction outputs for the Georgia HF radar data are verified using drifter simulation in Fig. 4. A drifter is a Lagrangian platform that drifts under currents without any other motion. Figure 4(a) shows trajectories of drifters under both observations and predictions, and we can verify the validity of the outputs by checking how close to each other these two trajectories stay. The separation error is shown in Fig. 4(b) to show how the error of the drifter trajectories under observations and predictions propagates by using further future forecast data. Compared to the separation results in S. Frolov et al., we've come to the close results to the ones using the West coast data.



(a) Error in vehicle speed



(b) Error in Vehicle velocity

Figure 5. Simulation results of Surrogate using Georgia coast HF-radar data

CONCLUSIONS/RECOMMENDATIONS (Heading 3, Times New Roman, 12 pt, bold)

We would like to extend the tradespace to evaluate the vehicle navigation performance in terms of both the prediction error and the environmental severity.

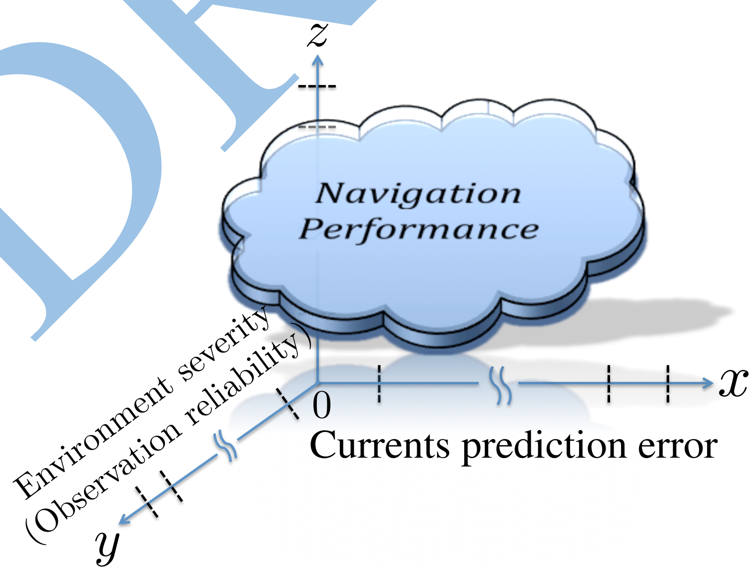


Figure 6. Tradespace for navigation performance associated with environmental severity and ocean model accuracy

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