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Data-driven Learning and Modeling of AUV Operational Characteristics for Optimal Path Planning

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Abstract— **Autonomous underwater vehicles (AUVs) are used to execute an increasingly challenging set of missions in commercial, environmental and defense industries. The resources available to the AUV in service of these missions are typically a limited power supply and onboard sensing of its local environment. Optimal path planning is needed to maximize the chances that these AUVs will successfully complete long-endurance missions within their power budget. A time-optimal path planner has been recently developed to minimize AUV mission time required to traverse a dynamic ocean environment at a specified speed through the water. For many missions, time minimization is appropriate because the AUVs operate at a fixed propeller speed. However, the ultimate limiting constraint on AUV operations is often the onboard power supply, rather than mission time. While an empirical or theoretical relationship between mission time and power could be applied to estimate power usage in the path planner, the real power usage and availability on an AUV varies mission-to-mission, as a result of multiple factors, including vehicle buoyancy, battery charge cycle, fin configuration, and water type or quality. In this work, we use data collected from two mid-size AUVs operating in various conditions to learn the mission-to-mission variability in the power budget so that it could be incorporated into the mission planner.**

Keywords— Autonomous Underwater Vehicles; Ocean Modeling; Path Planning; Data Assimilation; Machine Learning

I. INTRODUCTION

A. *Autonomous Underwater Vehicle Operations*

Autonomous underwater vehicles (AUVs) are increasingly being used in commercial, environmental and defense industries to monitor and sample oceanic processes and events [Bellingham and Rajan, 2007; Nicholson and Healey, 2008; Benjamin et al., 2010; Lermusiaux et al., 2016]. As the AUV technology has developed, a high safety margin has typically been applied to missions to minimize the risk that the AUV may get lost, encounter an obstacle, or run out of power before completing the mission. As autonomy theory and software allows the AUVs to become more independent, they are tasked to execute missions that challenge their performance and resource limitations, leading to the need of efficient planning systems [Kumar et al, 2005; Witt et al, 2008]. In particular, energy demands for these missions far outpace the incremental improvements in onboard energy storage capacity.

Given sufficient power and communications bandwidth, many AUV missions would be launched and recovered from shore to save on the expense of an accompanying vessel. The AUV would then need a transit plan that would ensure it arrives in the working area at an appropriate time, with enough energy to complete the task and safely return to the recovery point. As an example of the significance of the transit plan, consider that a 25% energy savings on a 500 mile transit at a typical AUV speed of 5 knots would allow two extra days on station in the working area. To unlock this increased mission

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efficiency, time- and energy-optimal path plans are needed.

For such optimized utilization to be most successful, the operational characteristics of the AUVs need to be modeled as accurately as needed by the optimization and specific needs of the ocean missions considered. The advent of machine learning and data sciences [Hsieh, 2009] as well as sensor fusion technique [Nicosevici et al, 2004] provide an opportunity to augment the classic engineering modeling and laboratory analyses by learning the AUV operational characteristics in situ, during and after each sea operations. Such data-driven learning is critical because, from mission to mission, the AUV usage frequently differs, the dynamic ocean environment changes, and the configuration of the AUV itself changes. For the latter, considering propelled vehicles, it is for example very common for fins and buoyancy to be modified, for payloads to be changed, and for the internal content and overall body of the AUVs to be altered [Rudnick, et al., 2004; Stokey et al., 2005].

In the present paper, we focus on the first research steps towards the capability of data-driven learning and modeling of operational characteristics of AUVs for time- and energy-optimal path planning. The fundamentals of such planning are discussed next.

B. *Time-optimal Path Planning*

A time-optimal path planner based on the level set method has been recently obtained by [Lolla et al., 2012; Lolla et al., 2014a, 2014b; Lolla, 2016]. The level set method writes the path-planning problem as the solution of the exact reachability-front-tracking Hamilton-Jacobi partial differential equation, given in (1).

$$\frac{\partial \varphi(\vec{x},t)}{\partial t} = -F(t)|\nabla\varphi(\vec{x},t)| - \vec{v}(\vec{x},t)\cdot\nabla\varphi(\vec{x},t) \quad (1)$$

In (1), the potential field is initialized such that it is convex with the zero-level contour at the starting point $\mathbf{x}_s$, $\varphi(\mathbf{x},0) = |\mathbf{x} - \mathbf{x}_s|$. For a flow prediction $v(\mathbf{x},t)$, and nominal AUV forward-speed in water $F(t)$, the zero level-set contour of the solution of (1) at time $t > 0$ is the time-optimal dynamic reachability front of an AUV starting from $\mathbf{x}_s$ [Lolla et al, 2014a]. The optimal arrival time T^* at a target $\mathbf{x}_f$ is the first time t at which $\varphi(\mathbf{x}_f,t)=0$.

Conveniently, the forward Hamilton-Jacobi form given in (1) specifies the levels φ in terms of the forward speed of the AUV $F(t)$ and the velocity of the underlying oceanographic flow $v(\mathbf{x},t)$. Given this forward reachability form, the fastest plan to reach a desired destination, assuming a particular AUV propulsion profile $F(t)$, can be determined through the following successive steps: 1) Initialize the potential function so that the zero level is coincident with the AUV starting location. 2) March the Hamilton-Jacobi equation forward in time, which will allow the zero level contour(s) to expand according to the combination of the AUV forward speed and the underlying dynamic oceanographic currents. 3) Determine whether the destination is inside the zero level contour(s). 4) If it is inside, then a time-optimal path is determined by back-propagating the vehicle's position from the final destination to the starting location.

C. *Energy-optimal Path Planning*

For energy-optimality, the path integral of the AUV power usage is minimized across all paths that arrive within an allotted time [Subramani et al., 2014; Subramani and Lermusiaux, 2016; Subramani et al., 2017]. An accurate model of the forward speed $F(t)$, which captures the engineering operations of AUV including interactions with the environment, is required to ensure valid results. The forward speed $F(t)$ is a potentially complex function of RPM, fin configurations, payload, and stability due to interaction with waves and near-AUV circulations. These complex interactions are then passed on to the instantaneous power of the AUV propulsion through the speed-power relationship.

The direct method to optimize for energy with this technique is to compute time-optimal paths across a distribution of vehicle speed and depth profiles, and then compute the energy expended while following all of the paths that arrive within an acceptable time frame. If the AUV propulsion-to-energy model is accurate, then selecting the least energetic of the time-optimal paths will yield an energy-optimal path within the allotted mission time.

II. APPROACH

The missing component in the time and energy optimization plan is mission data for an AUV over a variety of configurations. To meet this need, we mined the vehicle mission logs from several experiments with two specific vehicles under varying conditions. In this paper, we present an initial analysis of the speed-to-power relationships on these AUVs, using regression and time-series analysis. In future work, one could apply data-driven machine learning approaches, as utilized in Swezey (2016), to determine these relationships. Results of this work could also be used to serve other optimality criteria, such as optimal adaptive sampling or optimal surveillance [Bellingham and Willcox, 1996; Lermusiaux, 2007; Leonard et al, 2010].

A. *Available Mission Data*

The data utilized in the present study was collected through a series of sea exercises conducted in the Buzzards Bay, Vineyard Sound, and Martha Vineyard's region in southern Massachusetts (Figure 1) through 2015 and 2016, utilizing

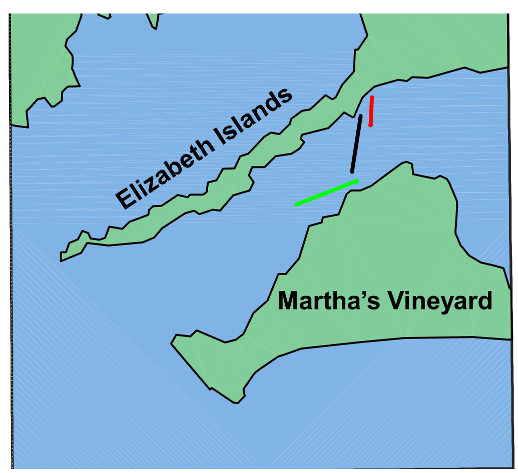

Figure 1. AUV paths during the December 2016 test, in the vicinity of Martha's Vineyard.

Remote Environmental Monitoring UnitS (REMUS) series AUVs. Tests were conducted alongside the Elizabeth Islands, near Weepecket Island in Buzzards Bay, and in northern Vineyard Sound, all using REMUS 600 AUVs.

During an AUV mission, a large number of variables may be monitored and logged. Included in this data log are:

- vehicle state variables, e.g. the position and attitude estimates of the vehicle,
- vehicle command data, e.g. the desired propeller speed,
- subsystem state data, e.g. remaining voltage and current demand on the battery, and
- onboard sensor data, such as an acoustic Doppler current profiler (ADCP) monitoring the local flow field around the AUV.

These data provide fertile ground for multivariate analysis of the relationships between logged variables and vehicle forward speed *F(t)* and power *p(t)*. In the present work, we select a subset of this data to examine the relationships between intuitively related pairs, such as speed-through-the-water and power usage, via regression analysis.

B. Data Selection

We seek to quantitatively investigate some of the expected relationships among the logged data. First, the data are screened to include only active mission information – the AUV must be at depth and actively propelling itself forward. There are additionally startup transient effects at the beginning of each mission that should be accounted for in each mission energy plan, but are separate from the near steady-state transit segment of the mission.

The directly relevant data for power calibration are speed through the water, or thruster RPM as a surrogate, and power demand on the battery. The expectation from these data is that there is a simple functional relationship between them that could be then used to compute the energy consumption along the time-optimal path plans. In general, such functional relationship can vary with several parameters related to the set-up of the AUV. Supporting data are used to investigate whether there are correlations between underlying data and deviations from the functional relationship.

III. DATA COLLECTION AND ANALYSIS

For this work, we use a series of several sea tests involving mid-size AUVs in the vicinity of Woods Hole, MA between October 2015 and December 2016. In the 2016 test, time-optimal plans, shown in Figure 1, were provided to the AUVs in different oceanographic flow regimes within the local region. For the purposes of AUV performance learning, these tests are data collections of opportunity; the mission plans were devised in service of other objectives, and the vehicle mission data were recorded to reflect the state of the AUV during those missions. There was no specific test objective to collect data to capture the different vehicle configurations, speeds and battery discharge characteristics. This on-line approach of data collection is to illustrate that such online mission data can be used for machine learning of the relevant operational characteristics and functional relationships. The AUV hulls employed in each of these tests of opportunity are the same, but the local oceanography and the AUV configuration varied according to the goals of the particular test. The test vehicles were mid-size, 12.5" diameter class AUVs. The particular models were Kongsberg/Hydroid REMUS 600s.

A. Speed versus Power

The first correlation to be made is between the forward speed of the vehicle and the energy consumption. To first order, the relationship between vehicle power consumption due to propulsion w_p and forward speed through the water v is expected to be $w_p=w_o+\kappa v^3$, where w_o is the hotel load of the AUV. In Figure 2, the raw vehicle speed through the water data are plotted versus the simultaneous battery power demand data for all data points during the missions of one of the AUVs, along with the best fit curve according to the assumed cubic relationship. The curve fit follows the data reasonably well, although there is clearly some significant variability revealed around the high density point cluster at 1.5 m/s and 20 W. There are also spikes in energy demand up to 60 W at the start and end of missions. These data points have been excised for the purpose of the curve fit.

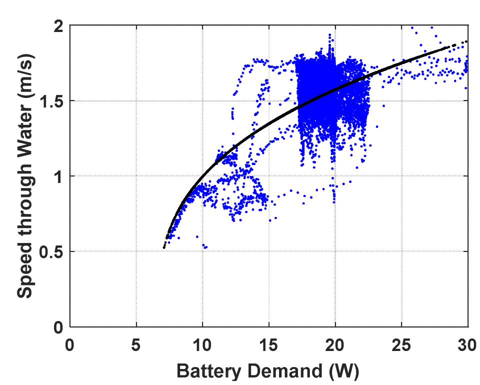

Figure 2. AUV speed through the water versus power demand on the battery. The black curve corresponds to the best cubic fit.

It was expected that the thruster RPM could be used as a surrogate for speed through the water, and the logged data support this assertion. The raw data, along with a linear fit of the data, are shown for vehicle speed over ground and through the water versus thruster RPM in Figure 3. This graph shows that the linear relationship to speed over ground is supported with a 0.44 R^2 coefficient. On the other hand, the disparity between the speed over ground and thruster RPM ($R^2 \sim 0.04$) illustrates the significance of the currents on the AUV forward progress.

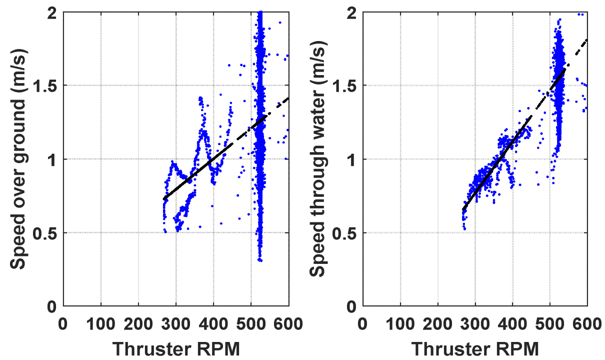

Figure 3. AUV speed versus thruster RPM. On the left is speed over ground, while speed through the water is shown on the right.

B. Other Vehicle States versus Power

To examine the correlations between other logged variables and the power demand, one-to-one regressions were computed for all of the vehicle, ADCP and battery states. As one would expect, the correlations were highest for current demand, closely followed by thruster speed. After the thruster-related states, the variables with the highest correlations were the fin control states. A summary of the linear coefficients of determination are shown in Figure 4.

The fact that these parameters show significant correlation to the power demand data indicates that there is information to be exploited by the path planner, either for energy-optimal path planning or for in situ adjustments.

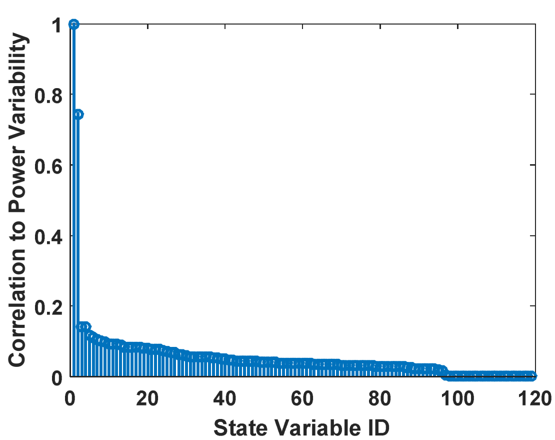

Figure 4. Correlation coefficients between vehicle power fluctuations and each of the logged state and sensor variables.

C. Variability versus Time

As the AUV executes its missions, it experiences a variety of local conditions. As a result, the fluctuations in power usage may vary due to the AUVs response to these local flow conditions. To test whether the speed or power fluctuations are correlated to logged vehicle data fields, cross-correlations between fluctuating components of the signals were used. The fluctuating components of the signals were made by removing the time-varying median of the measurements, using a median filter of short length so that the fine noise structure was maintained.

The results of the cross-correlation between AUV power consumption fluctuation and the fluctuations of each of 120 logged vehicle data components are shown sorted in decreasing order in Figure 4. In this figure, it can be seen that two state variables have a very high correlation to the power fluctuation. The first appears to be almost a direct measure, with correlation of 0.99. In fact, it is the current draw of the vehicle, so it is very tightly coupled to the power draw. The second highly correlated feature is more surprising; it is the ground fault indicator (GFI), which usually serves to alert the operator that there might be a leak in the hull, or some other potential short circuit. The GFI is directly monitoring the status of the electrical system, so its fluctuation is probably dependent on the vehicle power usage and not vice versa.

Beyond these two direct measures, the correlations decrease significantly. However, the state variables that are more correlated to the power are likely candidates: in decreasing order, the first several are thruster command, pitch goal, measured pitch, cross-axis acceleration, CPU load, distance traveled, depth goal and depth. The common denominator is that most of these are related to changes in the AUV trajectory. It is interesting to note that the most highly correlated components are directly measured, and that the estimated variables are largely absent. The lack of correlation in the noise of these estimated variables are likely a result of the smoothing effect of the filtering process in the estimator.

These correlations indicate that small-scale vehicle adjustments during its mission leave a measurable imprint on the power consumption. The low amplitude of the correlation coefficients suggests that there is a multivariate or nonlinear relationship to the underlying components.

IV. SUMMARY

In order to create energy-optimal path plans, a calibration of vehicle speed through the water to power consumption is normally used. This study of the logged state information across multiple sea trials confirmed that this procedure can capture a large part of the vehicle energy consumption during a mission. However, an inspection of the correlations among these state variables logged on an AUV revealed that there are relationships among the noise components of these variables that can be used to adjust this energy calibration.

In particular, the control commands to adjust pitch and thrust in response to local flow events has an impact that is directly seen in the instantaneous power usage. Based on these results, it is expected that a machine learning or similar nonlinear regression approach could be exploited to optimize path plans for energy, taking into account potential vehicle adjustments to the local effects during the mission. In the future, results can be employed for other types of optimal path planning and AUV missions, including optimal formation control [e.g. Fiorelli et al., 2006; Lolla et al., 2015], optimal localization and mapping [e.g. Leonard and Durrant-Whyte, 1991] optimal sensing [e.g. Heaney et al., 2007, 2016], and optimal surveillance [e.g. Kenma et al, 2011].

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