An Online Utility-Based Approach for Sampling Dynamic Ocean Fields

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Abstract—The coastal ocean is a dynamic and complex environment due to the confluence of atmospheric, oceanographic, estuarine/riverine, and land–sea interactions. Yet it continues to be undersampled, resulting in poor understanding of dynamic, episodic, and complex phenomena such as harmful algal blooms, anoxic zones, coastal plumes, thin layers, and frontal zones. Often these phenomena have no viable biological or computational models that can provide guidance for sampling. Returning targeted water samples for analysis becomes critical for biologists to assimilate data for model synthesis. In our work, the scientific emphasis on building a species distribution model necessitates spatially distributed sample collection from within hotspots in a large volume of a dynamic field of interest. To do so, we propose an autonomous approach to sample acquisition based on an online calculation of sample utility. A series of reward functions provide a balance between temporal and spatial scales of oceanographic sampling and do so in such a way that science preferences or evolving knowledge about the feature of interest can be incorporated in the decision process. This utility calculation is undertaken onboard a powered autonomous underwater vehicle (AUV) with specialized water samplers for the upper water column. For validation, we provide experimental results using archival AUV data along with an at-sea demonstration in Monterey Bay, CA.

I. INTRODUCTION

MANY of the complex multidisciplinary phenomena in the ocean that scientists seek to understand, such as algal or phytoplankton blooms, sediment transport processes and riverine and estuarine plumes, have uncertain spatial and temporal expressions. Recently, novel approaches to sampling have explored using cost-effective and capable robotic platforms such as autonomous underwater vehicles (AUVs) [41]. These vehicles can support a diverse array of sensors to resolve interacting physical, chemical, and biological phenomena. To get an informed view of this world, scientists need to obtain water samples from within targeted features of interest for shoreside analysis. Traditionally, this has been undertaken using ship-based approaches. At the Monterey Bay Aquarium Research Institute (MBARI, Moss Landing, CA), our Dorado AUV platform has been outfitted with a number of water samplers [5] (Fig. 1), with each canister used at most once during the course of a mission. While this has provided the required capability to return water samples, it poses the additional challenge of ensuring that water samples returned are taken within these features of interest. Doing so enables biologists to construct species distribution models where potential genetic variations can be captured.

The challenge we address in this paper is to return water samples effectively from locations near the centroid or boundary of the feature, control samples from the ambient environment, and to do so with a limited number of samplers while respecting spatial sampling constraints. The scientific intent of such sample return is to build models for microorganism species distribution and abundance. Returning water samples provides the necessary molecular methods with appropriate data. This is the first of many stages in understanding the distribution, community structure, and the phylogenesis of marine phytoo and zoo plankton, which are often at the bottom of the food chain [15], [42], [44].

The technical challenge is further amplified by the fact that we have no a priori models to guide our robotic sampling, in missions that last hours and cover several square kilometers.

The field to be sampled is dynamic and unknown a priori and the need to balance competing demands of maximizing science return with sampling constraints often forms the core of how one measures utility in this domain. For instance, triggering a water sampler early in the mission might have less utility given the fact that we expect to see a stronger feature signal. Conversely, at the end of the mission might result in oversampling or alternatively returning
with unused samplers; spatially distributed samples are therefore highly desirable. Often these sampling goals are soft constraints [2], [6] reflecting an “intent” rather than a hard requirement; for example, oceanographers would prefer that samples be returned even when sensors detect a weak feature signal over the course of the mission.

The novelty of our work is in providing a framework based on the calculation of sample utility by capturing preferences and constraints, which provide a balance between temporal and spatial scales of oceanographic sampling. Our approach integrates available information a priori and does so in such a way that science preferences or evolving knowledge about the feature of interest can be incorporated easily. The resulting techniques can be applied to any sequential sampling schema with any level of information about the feature; from having substantial information in real time, to having only an approximate model description, allowing an oceanographer to choose from a variety of utility functions depending on scientific needs and expected oceanographic conditions. The chosen functions are then installed into our onboard deliberative control system T-REX [29], [31], [36] to make effective use of AUV sampling missions. Details of the T-REX system and its interface to the utility functions are outside the scope of this paper. Utility impacts deliberation and not vice versa.

Our paper is structured in the following manner. Section II presents the specific scientific problem we are addressing and the challenges it poses. Section III lays out the problem description. Section IV highlights related work and places our work in the context of past efforts in the fields of robotics and artificial intelligence. Section V describes metrics for sampling quality that we use to show the impact of using this approach. The core of the paper in Section VI deals with the overall techniques. Section VII describes the experimental results in simulation using historical AUV field data as well as at sea. We conclude with Section VIII.

II. KEY CHALLENGES

Intermediate nepheloid layers (INLs) are fluid sheets of suspended particulate matter that originate from the seafloor [32]. They develop episodically from transport of the turbid bottom boundary layer [43], [44] and have a potentially significant role in the population connectivity of benthic species having pelagic larval stages. In doing so, INLs potentially play an important role in our understanding of the hydrodynamic and biological processes affecting the connectivity of natural populations. They impact not only our scientific understanding of coastal community structure, but challenge policy making for coastal ocean management, marine protected areas, and sustainable fisheries regulation [27]. INLs are characterized by high optical backscattering and low chlorophyll fluorescence.

Predicting when and where key oceanic processes that impact INLs will be encountered is problematic in dynamic coastal waters where diverse physical, chemical, and biological factors interact in varied and rapidly changing ways. Wind and buoyancy-driven forcing, flushing due to land drainage, bathymetric variations, presence of fronts and large tidal variations together combine to drive variability in this coastal domain. Pilot surveys and returning to sample dense feature signals previously observed are usually not viable in such an environment. Additionally, operational and scientific constraints driven by the need to make the most of stored energy on AUVs and to obtain coverage in this dynamic environment define the problem domain in which we are to sample.

Further, without a priori biogeochemical model defining these processes, it is often a prerequisite in coastal ocean studies to sample water masses efficiently with prompt sample return for analyses. Ship-based sampling methods with periodic deployments of water samplers require fewer restrictions on a number of samples. However, sampling is less precise, more taxing on the vessel and crew with repeated stops potentially in adverse weather conditions, and is ultimately not cost effective in comparison to deployments with robotic platforms.

Sampling with robots such as AUVs comes with its own challenges. In trying to solve a slice of the adaptive sampling problem for robotic sample acquisition in our problem domain, we encounter the following difficulties.

- The primary scientific drivers for our surveys are biologists who are interested in constructing species abundance and distribution models. Shoreside analysis of captured microorganisms using molecular probes and sandwich-hybridization assays [17], [18], [45] allows detection of crustaceans, polychaetes, and mollusks. Scientific constraints driven by the need to understand genetic variability and community structure in these microorganisms forces spatial constraints between individual sampling locations. Consequently, returned water samples which provide sufficient sampling coverage of the targeted volume are desirable.
- With no a priori model of a feature, our primary challenge is to fly “blind,” detect the feature of interest (INLs are the focus of this paper), and appropriately trigger our water samplers. Feature recognition based on unsupervised clustering approaches [13] and hidden Markov models using semisupervised approaches [8] have shown to be viable. In this paper, our emphasis is on showing how a utility-based multicriteria technique can provide a more refined use of limited water samplers. Sample acquisition is at local environmental hotspots, where a measurement exceeds a predefined threshold [25], [33], characterizing dense feature signals in the upper water column.
- Our sampling approach is constrained operationally; the feature must be sampled in one volume survey with the...
the primary objective of taking water samples at hotspots. Battery limitations together with high temporal variability of the studied feature phenomena prohibit the robot to perform a pilot survey as in [39] and [40] or constrained local exploration [12] within the confines of a volume. No synthetic views are available a priori.

- Onboard the robot, we have a limited energy source restricting missions to a maximum of 18 h and with ten gulper water samplers (Fig. 1), with each sampler to be used once during the mission to avoid contamination.

To overcome these constraints, we propose an approach to autonomous sample acquisition based on an online calculation of sample utility. A series of reward functions provide a balance between temporal and spatial scales of oceanographic sampling, and we do so in a way that science preferences or evolving knowledge about the feature of interest can be incorporated in the decision process.

III. PROBLEM DESCRIPTION

The problem we address is in effectively returning water samples with an AUV, while respecting spatial and resource constraints. We are constrained to following a lawn-mower pattern within a predefined volume since it provides biologists a simple way in which to reconstruct the transects of the AUV. This provides the basis for understanding how to visualize the spatial structure of the INL and the context of where the water samples have been acquired. The objective is to take water samples within local maxima of the feature of interest, usually near hotspots. These hotspots are often patchy with a significant spatial extent horizontally (in kilometers) and with small vertical scales (in meters) [32]. Fig. 2 shows an example of an INL restructured based on a traditional AUV survey. As noted in Section II, spatial constraints between samples to be acquired are imposed (e.g., ≥500 m, often with a limit of two samples per transect) to ensure biological diversity of the specimens collected within the volume sampled.

We call the volumetric distribution of a certain oceanic phenomena a field of interest (FOI). Let $Z' : \mathbb{R}^3 \to \mathbb{R}$ represent a scalar FOI such that $y = Z'(v)$ is the value of the FOI at a geographic location $v \in \mathbb{R}^3$. In our experiments, the FOI is an INL. We obtain the value of $Z'$ for the current traversed point by means of a mapping from multivariate measurements, such as optical backscattering and fluorescence, described in our earlier work in [13] and [30]. For a location $v_i$, we obtain a value $Z'(v_i) = y_{v_i}$ in the interval $[0, 1]$ indicative of the strength of the INL at that point. During a mission, the robot’s goal is to decide autonomously whether to take a water sample at a location. At the end of the mission, a number of samples would have been taken, represented by the vector

$$G = \{v_1, y_{v_1}, \ldots, v_g, y_{v_g}\}$$

where $v_j$ represents the location where the sample is taken and $y_{v_j}$ represents the value for the FOI at that location. $g$ represents the index of samples and $\mathcal{V}$ defines the total number of available water samplers (ten) on the robot, with $g \leq \mathcal{V}$.

We define $Q$ as a post-facto quality metric computed after all samples $G_j = \{v_j, y_{v_j}\}$ have been collected and one that provides us with a qualitative score for the set $G$ taken sequentially as the robot moves through the water column.

We consider three sampling strategies driven by available information that are a combination of online and a priori approaches.

- **Weakly informed** strategies use reactive near-term values, including current and past values of the FOI, sampling locations thus far in the mission, the number of samples taken, and mission elapsed time. In other words, they do not rely on spatially or temporally contextual data available beyond AUV sensor data.

- **Mission aware** strategies are more cognizant with additional knowledge such as the total estimated survey time and, in the case of AUV surveys, survey geometry including the number of AUV transects and/or the spatial resolution (or width) of the transects.

- **Feature aware** strategies can be used when substantial information is available a priori. For instance, if the volumetric distribution of a FOI is known, it could potentially lead to a sample acquisition strategy with additional contextural information, such as a synoptic view, which can aid in the sampling decision. Ways in which such information would be available include past missions data, theoretical or synthetic ocean models of feature distribution, satellite imagery, data from a recent low (spatial) resolution survey or extrapolated real-time data from moorings and drifters.

In this paper, we focus on weakly informed and mission aware strategies and the description of:

1) a quality metric $Q$ to evaluate the resulting samples $G$ taken by a robot (1); the metric targets spatial coverage, patchiness, and feature intensity;

2) a framework to integrate the available information, and scientific and operational preferences to decide whether to take a water sample at a given location.

IV. RELATED WORK

Work on sampling design to monitor spatial phenomena spans the fields of ecology, earth science, statistics, diagnosis, and robotics. In ecology and earth science, the general aim is to determine the minimum set of sampling locations to characterize...
certain phenomenon (e.g., concentration of pollutants or spatial distribution of a biological species). Most of these efforts either have a priori knowledge of the FOI or can make assumptions about feature strength; however, our work is driven by discovery of this field as the mission progresses with no quantitative expectation of the FOI.

In the simplest cases, random or geometrical sampling designs are sufficient to specify the places where samples have to be taken to reconstruct $Z'(v)$. Usually tools from environmental or spatial statistics are used to choose the spatial sampling design. The FOI to characterize can be static or dynamic [characterized by $Z'(v; t)$]; most literature, such as [21], assumes a static field.

Sampling strategies can be model based or model free. Many assume a spatial model of the phenomena being observed. Often $Z'$ can be modeled as a random process with a joint Gaussian probability distribution over the measurable locations as in [11], [21], and [22]. In other cases, sampling design is based on descriptive statistics of the field being observed; for example, in [37], observed variance of the field within gridded regions is used to adapt sampling criteria. Given the existence of a probabilistic model for $Z'$, most efforts derive a priori selection of sampling points, based, for example, on the maximization of Shannon entropy [55], of mutual information among samples [4], [21], or on spatial patterns [9]. Once selected, samples are used to improve the model of $Z'$. In cases where the parameters of the random variable are not fully known or have a high degree of uncertainty, refinement of parameter estimation occurs as samples are taken [19]; past samples are therefore taken into account to decide future sampling locations. This is often known in the literature as adaptive sampling.

Adaptive sampling has been widely explored in the robotics literature. Approaches have targeted applications such as static sensor placement [3], [14], [20], [53] and path planning for mobile sampling platforms [4], [26], [52]. Usually the sampling approach is targeted at field reconstruction, where the goal is to be able to estimate the field at unobserved locations over a wide area. But it can also be focused on observing hotspots of $Z'$ [54], or on following a given spatial pattern [26], [47]. In [37], model-free approaches were used to guide a cable-guided robot to sample environmental fields. In [52], a pilot experiment with static nodes provided a sparse sample of an environmental field, from which a nonparametric spatial model of the field was computed. The task is then formulated as an orienteering problem and the solution path results in maximum reduction in reconstruction error with a bound on the energy consumption of the robot. In [21], given an initial sparse sample of a scalar field, a Gaussian process model is computed and a mutual information criterion is used to compute optimal sensor locations. In [4], the mutual information criteria are used to obtain informative paths for AUVs.

Most related work, as above, focuses on field reconstruction leveraging oceanographic or statistical models. Using these models, the trajectories of AUVs or gliders can be planned, often online [12], [16], [23], [51], to improve the quality of the estimates. The metric used is the field reconstruction error for the estimated field. However, many scientific applications require retrieval of samples from the field for lab analysis. Fox et al. [13] and McGann et al. [30] use an unsupervised clustering approach for sampling the water column. Learning data are unlabeled and the identification outcome ignores signal history so that it depends only on the data sensed at an instant. Celorrio et al. [8] extend this work to include a temporal component using hidden Markov models. In [54], special characteristics of the feature to be sampled, in this case horizontal distribution of an oceanic feature, are used to predict close future values for water sample acquisition. They look for peak chlorophyll values within thin layers constrained by vertical structure in the water column. In [53], empirical orthogonal function (EOF) analysis is performed on historical data, and sensors are placed such that the EOFs show large magnitudes at sensor locations and cross product between EOFs is small between selected locations.

Previous efforts like [23], [24], [39], [48] reduce model uncertainty via assimilation of newly acquired data into an a priori model. Given the background covariance function learned from past data, new data obtained from vehicle deployment estimate the field at unobserved locations using methods similar to Gaussian process regression (GPR) and kriging [28], [38]. As in kriging and GPR, the uncertainty estimate of prediction is dependent only on the location and time and not on the actual field value. Hence, a priori design is possible. Additionally, in [23] and [24], using an a posteriori error, near-optimal glider trajectories are computed. The existence of a prior and field reconstruction needs distinctively diverge from the drivers of our efforts.

In the diagnosis community, the placement of sensors has been explored widely as a means to drive the minimal set of probes for fault detection and isolation [7], [34]. The key idea is to find a minimum number of probes and yet be able to reasonably identify anomalies in systems, including networked traffic and electronic chips, being monitored. These probes are used to discriminate a discrete and finite set of signals quite unlike the continuous and complex fields in the coastal ocean.

V. QUALITY METRICS

A. Background and Previous Work

To measure the effectiveness of a survey, the objective and the metric that is designed need to be well coupled [50]. In our previous work [13], [30], we measured the effectiveness of a survey by querying the scientist for post-facto selection of sample locations in the field. The selected sample locations constituted what we could consider the optimal samples set $G$. Once a set $G$ was selected, any other sample set $G$ could be compared by using a geometrical distance metric between points in both sets. However, manually marking points after a mission is onerous, therefore we would like to have a metric that:

- does not require an optimal set $G$ to be defined by hand;
- balances sampling hotspots with coverage, adapting to scientific preferences.

In the adaptive sampling community, the sampling goal is usually to reduce the uncertainty in $Z'(v)$, $\forall v \notin G$ [16], [23], [35], [48], [50]. Doing so allows the few samples taken to be representative of those not part of the sampling pool. Thus, when the goal is field reconstruction, sampling strategies are evaluated by a measure of how much information about the field the
samples capture. Some of the metrics used are field entropy [26], or field reconstruction error measured as squared error between estimated field and true field [23], [35], [48], [50], [52]. However, these metrics are not applicable to our problem since our objective is not field reconstruction.

A general methodology to define a quality metric that compares different sampling designs is to assume that, for a given sampling goal, there is an optimal sample set \( G^* \) [23]. The objective of a quality metric then is to characterize the performance of a certain sample set \( G \) when compared with \( G^* \). For example, a metric can be designed that assigns a normalized score of 1 to the optimum sample set \( G^* \). A certain choice of sampling points will produce a sample set \( G \) with score \( s \leq 1 \). We can now use this score to compare how different sampling strategies perform. Alternatively, a distance measure can be designed to rank any \( G \). The closer to \( G^* \) a certain \( G \) is, the better. It is also possible to design a metric that does not need an optimal solution \( G^* \) to be set \( a \) priori. In those approaches, a metric is not calculated as a distance to a certain optimal solution, but is intrinsic to each solution.

Consider a 2-D field depicting a horizontal slice of an INL as shown in Fig. 3 from an AUV survey on June 26, 2008 (mission 2008-06-26). Suppose that our goal is to retrieve water samples from within patches of high intensity signal. A baseline case is where we perform uniform sampling, i.e., spread over all discrete samples in space resulting in a sample set marked by circles in the figure. On the other hand, the squares would represent what would ideally rate as a “good” sample set given the scientific intent of sampling in hotspots while maintaining spatial coverage. The question to be posed then is what metric would be set \( a \) priori. Those approaches, a metric is not calculated as a distance to a certain optimal solution, but is intrinsic to each solution.

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values would be the same for all the regions, with the intuition that samples have been taken representing regions that capture the same signal intensity.

- \( cv_\mu \) is the coefficient of variation of the mean value of \( Z'(v) \) for each Voronoi region. This measure balances the two metrics above: like \( cv_\Sigma \) it accounts for the values of the feature within each region, but unlike it, the size of the regions matters. For example, two regions, one large with low feature strength and one small with high feature strength, will yield a low value for \( cv_\Sigma \), a high value for \( cv_A \), and an intermediate value for \( cv_\mu \). If all the regions were equal in area, \( cv_\mu = cv_\Sigma \); if all encapsulated the same feature signal, \( cv_\mu = cv_A \).

The best theoretical value for \( cv_A \) is obtained when all the areas of the Voronoi partitions are equal, so \( cv_A = 0 \) and the selected sampling points partition the survey area in equal sub-areas. The worst case is when all the subareas are zero except one, which occupies all the survey. In that case, the standard deviation is \( a/\sqrt{n} \), where \( a \) is the total survey area and \( n \) is the number of samples. As the mean area of the Voronoi partitions is always \( a/n \), the worst case value for \( cv_A \) is \( \sqrt{n} \). Consequently, the range for \( cv_A \) is \( 0, \sqrt{n} \). The same applies for \( cv_\Sigma \); in theory, the worst case is when one of the partitions has all the concentrated FOI while other partitions have none, so \( cv_\Sigma \rightarrow 0, \sqrt{n} \). It is not difficult to calculate that \( cv_\mu \rightarrow 0, \sqrt{n} \). These ranges are an upperbound, depending on the spatial distribution of hotspots.

Figs. 4 and 5 graphically show maximum and minimum values for each of the metrics for the 2006-08-26 and 2009-11-09 AUV missions. In Figs. 4(a), (c), and (e) and 5(a), (c), and (e), sampling is marked at hotspots maximizing the metric (i.e., lower values), given the hotspots detected and the survey geometry. The squares represent where the samples are taken, and the triangles represent all the possible hotspots for that mission. In Figs. 4(b), (d), and (f) and 5(b), (d), and (f), the worst case values for the metric and the hotspots yielding this value are shown. In both figures, the Voronoi partitions resulting from sampling at these hotspots are also shown. Note that all the six sample sets shown in each figure address our primary scientific goal: returning water samples from hotspots of a FOI, an INL. The difference lies in how obtaining samples at those locations partitions the survey area, which is our secondary goal.

Evaluating these metrics online effectively is challenging. Not only is computing Voronoi partitions computationally intensive, but also knowledge of all sample location points a priori is necessary. As a result, we focus on locally available information in situ, augmented by science-driven intent and FOI estimates to drive our sampling. In Section VII, we compare the above metrics.

VI. TECHNICAL APPROACH

A. Previous Work

Our previous efforts in sample acquisition [13], [30] used an a priori triggering threshold, \( T_f \in (0, 1) \), based on the estimated value of the FOI \( Z'(v) \). Consequently, this method was reactive with no means to balance the competing needs of cov-

erage with either weakly informed or mission aware methods. The threshold was chosen by a scientist for each mission based on seasonal variation and oceanography, taking into account his expectation about a FOI strength high enough to be of interest for sample acquisition. A hotspot was defined as any local maximum with value equaling or exceeding the threshold. To detect peaks, a classical gradient tracking mechanism [49] was used: a maximum being the point where the slope of the FOI value flipped from positive to negative. The first sampler was triggered as soon as a peak was detected and \( y_b \geq T_f \), so a water sample was always taken at the first detected hotspot. The procedure used in this work can be formalized as follows: as the robot traversed the water column we continuously evaluated a function \( u \) at 1 Hz, representing the potential utility of a sample taken by a robot at location \( v \).

\[
u(v) : \mathbb{R}^3 \rightarrow [0, 1] \subset \mathbb{R}.
\]

This utility is an online estimation of how sampling at \( v \) alters the quality \( Q \) of the sample set. In other words, if \( G = \{ (v_1, y_1), \ldots, (v_g, y_g) \} \), is the vector of samples already acquired, the utility estimates the quality of the set with the addition of \( (v_{g+1}, y_{v_{g+1}}) \). If the utility was higher than the triggering threshold, a sample was acquired. Since the acquisition policy was to acquire samples at local maxima and to detect a maximum we used a gradient tracking mechanism, this threshold-based approach can be defined as

\[
F = \{ v_n \geq T_f \wedge u_v < u_{v_{n-1}} \}
\]

where \( F \) depicts whether a sample should be acquired, \( T_f \in (0, 1) \) is the trigger threshold, and \( u_v \) is the utility at the previous location. Science needs also dictated a minimum separation distance between samples \( d_{\text{min}} \); so given a possible sample location \( v \) and the set of previous samples acquired \( G \), the utility was given by

\[
u(v, G) = \begin{cases} 0, & v \in \{1 \ldots g\} : \text{dist}(v, v_i) \leq d_{\text{min}} \\ y_v, & \text{otherwise} \end{cases}
\]

where \( g \) is the number of samples already acquired, \( v_i \) is the location of the sample \( G_i = (v_i, y_{v_i}) \), and \( \text{dist}(v, v_i) \) is the Euclidean distance between locations \( v \) and \( v_i \).

This approach has the following drawbacks.

- The sampling policy is myopic [19]. For patchy fields where hotspots are distributed spatially, the policy results in greedy sample acquisition as long as the minimum separation constraint \( d_{\text{min}} \) is satisfied. This can potentially result in all samples being acquired early in a mission.

- The spatial constraint \( d_{\text{min}} \) is a hard constraint. Not only is it enforced irrespective of signal strength, but also it is challenging to find a “good” value in the first place. What is desirable instead is the expression of scientific “intent” such that the constraint can be relaxed in cases where potential samples with high information gain can be closer than a \( d_{\text{min}} \) specified for the mission.

- Finally, such a policy is also constrained by the threshold \( T_f \) chosen a priori. This is a significant drawback in situations where acquiring a sample with low utility is consid-
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Fig. 4. Best and worst case values for each of the three metrics, for an AUV mission on June 26, 2008. In the left-hand side panels, samples have been taken at hotspots maximizing the metric; for those hotspots, the metric value is as low (better) as it can be for that mission. The squares represent where the samples are acquired, and the triangles represent all the other possible hotspots for that mission. In the right-hand side panels, the worst case values for the metric and the hotspots yielding this value are shown. The Voronoi partitions resulting from sampling at these hotspots are also represented. $\gamma$- and $\chi$-axes are northing and easting (in kilometers). (a) Best possible value for $cv_A$. (b) Worse possible value for $cv_A$. (c) Best possible value for $vc_\Sigma$. (d) Worse possible value for $vc_\Sigma$. (e) Best possible value for $\epsilon v_p$. (f) Worse possible value for $\epsilon v_p$.

erably better than no acquisition. This is especially true if toward the end of a mission samplers are still available. To address these drawbacks, we show a general framework with the goal of integrating science preferences with informa-
Fig. 5. Best and worst case values for each of the three metrics, for an AUV mission on November 9, 2009. In the left-hand side panels, samples have been taken at hotspots maximizing the metric; for those hotspots, the metric value is as low (better) as it can be for that mission. The squares represent where samples are acquired, and the triangles represent all the other possible hotspots for that mission. In the right-hand side panels, the worst case values for the metric and the hotspots yielding this value are shown. The Voronoi partitions resulting from sampling at these hotspots are also represented. Y- and X-axes are northing and easting (in kilometers). (a) Best possible value for $cv_A$. (b) Worse possible value for $cv_A$. (c) Best possible value for $cv_Y$. (d) Worse possible value for $cv_Y$. (e) Best possible value for $cv_Z$. (f) Worse possible value for $cv_Z$.

Another way to calculate utility during the course of a mission. By doing so we add contextual information to the policy presented in [13] and [30]. Sample utility is now a function of time and space, in addition to being dependent on the signal strength.
B. Utility Calculation in Sequential Sampling

Generalizing our previous work, we define a sampling utility function \( u \) as

\[
u : \mathbb{H}^3 \rightarrow [0, 1] \subset \mathbb{H} = f_{\text{goal}} \times f_2 \times \cdots \times f_n \tag{5}\]

where \( f_s \) is a reward function representing a specific constraint or “behavior” that should affect the total sample utility while targeting desired properties of the sampling policy. \( f_{\text{goal}} \) represents the key science goal of acquiring samples at hotspots; for our application, \( f_{\text{goal}}(v) = y_v \).

Using this framework, new parameters or “behaviors” can be included in the utility calculation, making it configurable and adaptable to changing scientific goals. The multiplicative utility has the effect of allowing any of the objective functions to act as hard constraints. Additionally, since each reward function addresses a different property or requirement for the overall sampling task, they can be decoupled and modeled in isolation one from another allowing for a flexible experiment design.

We focus on weakly informed and mission aware strategies where \( y_v \) is only known for present and past locations, using the following.

- **Weakly informed rewards**
  - distance to previous samples \( f_{\text{dist}} \);
  - number of samplers used \( f_{\text{sampler}} \).
- **Mission aware rewards**
  - remaining time and number of remaining transects in a volume survey \( f_{\text{static}} \).

Scientists can decide whether to include a reward function when the corresponding behavior is desired in the sampling strategy. In our current implementation, utility is defined as

\[
u(v, G, t) = y_v \times f_{\text{dist}} \times f_{\text{sampler}} \times f_{\text{static}}. \tag{6}\]

A suitable function profile encapsulating science preferences has to be designed for each of the reward functions above. Each reward function has a series of parameters in order to fine tune the desired behavior. For example, \( f_{\text{dist}} \) is the reward function bringing in spatial constraints between samples into the utility calculation. Its parameters allow these constraints to be more relaxed or strict depending on science needs. To ease the scientist’s effort, a series of predefined, ready to use, function profiles have been generated. These profiles are combinations of function parameters that encapsulate typical cases the scientist would be interested in, with new profiles synthesized as needed. Fig. 6 shows the six predefined profiles implemented for \( f_{\text{dist}} \rightarrow [0, 1] \subset \mathbb{H} \). This reward function modifies the utility taking into account the distance to the nearest previous sample. If this distance is more than a certain \( d_{\text{min}} \), the utility is not modified (i.e., the reward is equal to 1). If it is lower, a reward \( g(d) \) is returned. Doing so, it dynamically reduces the utility of taking a water sample at a location when it is closer than \( d_{\text{min}} \) to any previous sample.

Formally, \( f_{\text{dist}}(v) \) evaluated at location \( v \) is

\[
f_{\text{dist}}(v) = \begin{cases} 
0, & d \leq d_{\text{strict}} \\
g(d), & d_{\text{strict}} < d < d_{\text{min}} \\
1, & d \geq d_{\text{min}} 
\end{cases} \tag{7}\]

where \( d = \min(d_{\text{dist}}(v, v_i)) \) \( \forall G_i \subseteq G \), where \( G_i \) is a previous sample with location \( v_i \); \( d_{\text{strict}} \) is the Euclidean distance constraint to be enforced between samples; and \( g(d) \) is a monotonically increasing function of the distance, such as \( g(d) \leq 1 \), if \( d_{\text{strict}} < d < d_{\text{min}} \). \( f_{\text{dist}} \) is fully specified with parameters \( d_{\text{min}}, d_{\text{strict}} \), and \( g(d) \). The minimum distance \( d_{\text{min}} \) is usually selected taking into account the total spatial area covered by the survey, while \( d_{\text{strict}} \) is a percentage of \( d_{\text{min}} \); the lower its value, the more relaxed the spatial constrains are. The vertical axis in Fig. 6 shows the reward and the horizontal axis shows the distance to the nearest sample, expressed in percentage of \( d_{\text{min}} \) (100% implies that the distance = \( d_{\text{min}} \)). In all the cases, the reward grows as the distance increases, and equals at most 1 when the distance is equal or larger than the minimum distance threshold. As an example, for profile #2, \( d_{\text{strict}} = 0 \) and \( g(d) = d/d_{\text{min}} \), while for profile #3 \( d_{\text{strict}} = d_{\text{min}}/2 \) and \( g(d) = d/d_{\text{min}} \).
with \( g \) being the number of samples already acquired, \( M \) the total number of onboard samplers, \( g_{\text{min}} \) the number of samples taken before the threshold is increased, and \( k \in [0, 1] \) the rate of change of the increase. Higher the \( k \), the more the threshold is increased from one sample to the next. For example, in Fig. 7, for profile #7, \( g_{\text{min}} = 1 \) and \( k = 0.2 \), while for profile #10, \( g_{\text{min}} = M/2 \) and \( k = 0.2 \).

Mission aware utility functions integrate knowledge about the specific mission. In the context of AUVs, remaining time and number of pending transects are taken into account to define a reward function, \( f_{\text{ratio}} \). Usually both parameters are balanced, allowing a mission to be completed in the available time. Coastal conditions, especially currents, can make AUV speed and routing unpredictable. In addition, the onboard planning module adapts the sampling area resolution dynamically, increasing it in areas with high FOI signature and vice versa in areas of low signature [29]. With the onset of mission end, \( f_{\text{ratio}} \) has the effect of increasing the utility of sample acquisition and is complementary to \( f_{\text{samplers}} \), the former ensures balance in acquiring too many samples early in the mission, while the latter reduces the threshold of the signal strength required toward mission end for acquisition. Formally

\[
f_{\text{ratio}}(Q, R) = \begin{cases} 
\frac{R}{Q} & \text{if } R > Q \wedge R \geq u_t \wedge Q > 0 \\
1 & \text{otherwise}
\end{cases}
\]  

(9)

where \( Q = g/M \), \( R = \max(t_i/t_{\text{total}}, d/e) \), \( t_{\text{total}} \) is the maximum mission time, \( t_i \) is the current time, \( d \) is the distance already traveled, \( e \) is the total estimated distance to be traveled, \( g \) is the number of samplers used, and \( M \) is the total number of samplers. \( a_t \) is the activation threshold and is the only parameter of this function; \( f_{\text{ratio}} \) is not activated until \( a_t \) is reached. For example, in our current implementation, \( f_{\text{ratio}} \) is 1 until at least 40% of the mission has been acquired (\( a_t = 0.4 \)). The percentage of mission completed, in terms of time and distance, is calculated and compared to the percentage of samplers used thus far. If the former is larger, it increases acquisition likelihood by increasing utility. The aim of this reward function is to force all the samplers to be activated by the end of the mission even if the FOI intensity is low. Both \( f_{\text{dist}} \) and \( f_{\text{samplers}} \) quantitatively reduce utility, as their range is \([0, 1]\). In contrast, \( f_{\text{ratio}} \to 1, 10\) \(^2\) (when using \( f_{\text{ratio}} \), results in \( u > 1 \), \( u \) is truncated to 1) making the overall utility more permissive as we get closer to mission end.

The rationale for how these functions were designed is based on a mix of our knowledge of FOIs and operational and scientific constraints in our domain of operating the AUV. However, the methodology of their use is general (in Section VIII, we cover a number of ways to synthesize these functions, some automatically to overcome some limitations). \( f_{\text{dist}} \) originated from the need to relax the hard distance constraints in [30] (4). \( f_{\text{samplers}} \) resulted from the need to conserve samplers: the more samples one had acquired during the course of the mission, the

\[f_{\text{samplers}}(g) = \begin{cases} 
1, & g < g_{\text{min}} \\
1 - k \times \frac{g}{M}, & g \geq g_{\text{min}}
\end{cases}
\]  

(8)

Also, this formulation can encapsulate the approach in [13] and [30] expressed in (3) and (4) if we define \( u(v) = y_v \times f_{\text{dist}}(v) \) where \( d_{\text{strict}} = d_{\text{min}} \) and \( g(d) = 0 \), which corresponds to profile #1 in Fig. 6.

Fig. 7 shows the pool of predefined profiles designed for \( f_{\text{samplers}} \to [0, 1] \subset \mathbb{R} \), which takes into account the number of samplers. As the number of available samplers decreases monotonically during the course of the mission, \( f_{\text{samplers}} \) raises the cost of sample acquisition. This can be seen as a kind of threshold adaptation mechanism [12], [51], [54], since increasing the cost of acquiring samples using this reward function is equivalent to increasing the triggering threshold \( T_f \). The only difference is that \( f_{\text{samplers}} \) monotonically increases the threshold. The formal specification of this function is

\[f_{\text{samplers}}(g) = \begin{cases} 
1, & g < g_{\text{min}} \\
1 - k \times \frac{g}{M}, & g \geq g_{\text{min}}
\end{cases}
\]  

(8)

\[^2\text{To calculate the range of } f_{\text{ratio}}, \text{ the maximum value of } R/Q \text{ has to be calculated. Note that } R \to [0, 1] \text{ and the minimum value of } Q \text{ is } 1/M, \text{ when only one sample has been taken. In our case, } M = 10, \text{ so the range of the function is } [1, 10].\]
larger the FOI value of $Z'$ was needed to acquire the next set of samples. This could lead to some samplers not being used and is compensated by $f_{\text{ratio}}$, which modifies the utility, so lower values of $Z'$ are appropriate when closer to mission end. Both $f_{\text{ratio}}$ and $f_{\text{sampler}}$ play the role of threshold adaptation; the former decreases it at the end of the mission while the latter increases it each time a sample is taken. They could be combined in a single function, similar to that of [54], but we have opted to decouple them, allowing a scientist to make the selection.

1) An Illustrative Example: Suppose we want to adapt the threshold, so each time a sample is taken, the threshold is increased. For such a case the utility would be $u(v, G) = y_v \times f_{\text{sampler}}$, to take into account the remaining samplers. One can use profile #7 from Fig. 7 to evaluate online a discrete function of the form $f(g) = 1 - 0.2 \times g/M$, where $M = 10$ and $g$ is the number of samples previously acquired. This ensures that toward the end of the mission, $Z'$ has to be substantially over the trigger threshold $T_f$ for sample acquisition. For instance, if $T_f$ is set to 0.5 and for the current location the FOI $y_v$ is 0.51, then for the first sampler to be triggered $f_{\text{sampler}}(0) = 1$ and $u = 0.51$. Subsequently in the mission, if $y_v$ continues to be 0.51, with only nine samplers remaining, $f_{\text{sampler}}(1) = 0.98$ and $u = 0.4998$ with no samples being acquired. To trigger a second sampler, a stronger signal with $y_v > 0.50/0.98 = 0.5102$ will need to be observed. Therefore, for the tenth sampler to be triggered, $f_{\text{sampler}}(9) = 0.82$ so $y_v > 0.50/0.82 = 0.61$. One challenge of using this reward function is in determining the choice of $k$; a high $k$ will make it difficult to acquire samples late in the mission, while a low value will have almost no impact.

C. Discussion

Given lack of a priori information about the FOI, the use of reward functions allows incorporation of user preferences (as in the case of $f_{\text{dist}}$) or available knowledge about the mission, for sample acquisition. The knowledge can be gathered online (as in $f_{\text{sampler}}$), a priori, or as a mixture of both (as in $f_{\text{ratio}}$). In our case, survey geometry and total mission time, already embedded in $f_{\text{ratio}}$, are the only pieces of information available prior to an AUV mission.

The primary advantage of our approach is that it can be easily adapted to available knowledge or a scientist’s preferences. Further, it allows activating or deactivating specific rewards according to the mission at hand. If in the example above the scientist would also like to enforce spatial constraints or to decrease the threshold toward the end, it can be implemented by activating $f_{\text{dist}}$ and $f_{\text{ratio}}$, respectively. Or if a model of the feature were available, a reward function encapsulating this model could be added.

We face two primary challenges in our approach: the a priori definition of the triggering threshold for hotspot detection and the function profile selection. Variance in the threshold value will result in premature use or empty sampler return. However, we overcome this potential shortcoming by using the threshold adaptation mechanisms implemented by $f_{\text{sampler}}$ and $f_{\text{ratio}}$. To understand this variation and its impact, we undertake threshold sensitivity analysis in Section VII-B. To aid the selection of reward functions, in Section VII, we compare performance of different parameterizations with the metrics defined in Section V, in addition to comparing with our previous work in [13] and [30]. We also show whether different parameterizations for the same function behave differently and which parameters are better suited for a given mission or a family of missions.

VII. EXPERIMENTAL RESULTS

Using previous AUV data from missions in the Monterey Bay, CA, we provide a comparison between samples taken by means of a nominal nonutility-based approach, and those taken using utilities computed out of a set of reward functions. We show the results of applying our methodology [44] in a single field trial onboard MBARI’s Dorado AUV, carried out in July 2010 and applied to the science goal of sampling INLs.

Table I is a qualitative synopsis of missions used for this analysis. All but July 2010 (2010-07-01) are based on the approach shown in [13] and [30]. The table includes the triggering threshold selected by an oceanographer, the number of hotspots found given that threshold, the number of water samples taken, the duration of the mission, the absolute distance constraint imposed between samples, as well as a brief description of the FOI and the spatial distribution of the samples. For each mission, the threshold was chosen by a scientist according to expectations about FOI strength based on prior experience. A sensitivity analysis on the impact of this threshold in the number of hotspots is presented in Section VII-B. In all missions except that of July 2010, each sample involved the triggering of two samplers simultaneously to satisfy the need for the sample volume required for lab analysis. Hence, for these missions, five samples depict triggering of all ten samplers onboard the AUV.

Our historical data analysis involves simulating the AUV using past runs and following the same mission structure deterministically with identical sensor inputs for the FOI. Instead of triggering sample acquisition using the technique in [30], we use reward functions. Since there are six different predefined distance profiles, seven sampler profiles, and an on/off for $f_{\text{ratio}}$, a total of 84 different sampling profiles, including the nominal approach, were generated for each mission. These 84 profiles are compared in terms of the three defined metrics $cv_A$, $cv_{\Sigma}$, and $cv_{\mu}$.

A. Analysis of Results

Table II shows the quality metrics for each nonutility-based approach cited in [30]. For comparative analysis, experiments were run with a set of parameters highlighting a set of predefined reward function profiles for the same data set. For each metric, the best values are highlighted in bold. Lower $cv_{\Sigma}$, $cv_A$, and $cv_{\mu}$ (Section V) imply that the sampling policy is capturing both hotspottedness [26] and spatial coverage of the FOI $Z'$. In some missions (e.g., 2009-11-04), a combination of reward function profiles exists, which gives better values than the nonutility version for all three metrics.

From the above experiments and as shown in Table II, we determined empirically that for $f_{\text{st}}$ profiles #2 and #3 generated almost identical results. Also performance of profiles #1 and #5 is almost equal, and the same applies for #4 and #6. This is true for all ten missions for profiles #2 and #3, for eight out of ten
missions for profiles #1 and #5, and for nine out of ten missions for profiles #4 and #6. Profile #2 when used in near proximity with a previously sampled location generates an absolute utility, which is not substantially different had profile #3 been used, irrespective of signal strength. Similarly for profile #1; unless the threshold is equal or lower than 0.5, it resolves identically to profile #5 again irrespective of signal strength. As most of the missions have a threshold of at least 0.45, profile #5 resolves identically to profile #1 except for peaks where $\gamma (r) > 0.9$, which appear rarely in our experiments. The conclusion then has been to merge some of these profiles keeping only profiles #1, #2, and #4, and thus reducing the burden of choice for the scientist before planning a mission.

For $f_{\text{samplers}}$, profile #9 does not appear in experiments in Table II. Our intuition is that it is too aggressive, requiring a strong signal to take the last sample (it multiplies the value of $y_t$ by 0.5). A less aggressive equivalent, profile #12, appears in one result in the table; this appears only because it starts reducing the utility after at least half of the samplers have been used; thus, its value is always 1 in this mission, as less than half of the samplers were used. So except for missions with a very low threshold, our results do not support the use of those two profiles for $f_{\text{samplers}}$, and therefore, have been removed from the list of predefined parameterizations.

From all the missions in Table I, we consider two with different FOI characteristics to highlight our approach. Fig. 8 shows the samples taken during mission 2008-06-26 using the predefined reward functions $f_{\text{fist}}, #1$ and $f_{\text{samplers}}, #8$ from Figs. 6 and 7. It also depicts the total utility based on function choices and FOI values. As shown in Fig. 8, the AUV encountered a feature intensive FOI, with a total of 54 hotspots, leading to the use of almost all samplers early within the first 30% of the mission. However, this resulted in missing a more promising sampling location (with feature signature in excess of 0.9) toward the middle of the mission. Analysis with utility function combinations shows that no choice of functions could obtain quantitatively better values than the mission as sampled originally for all the three metrics ($c\gamma_t$, $c\gamma_A$, and $c\gamma_H$) simul-

### TABLE I

<table>
<thead>
<tr>
<th>Mission</th>
<th>Trigger threshold</th>
<th># of hot-spots</th>
<th># of samples</th>
<th>Mission Duration</th>
<th>Distance constraint</th>
<th>FOI Description</th>
<th>Sample Distribution</th>
</tr>
</thead>
<tbody>
<tr>
<td>2008-05-12</td>
<td>0.52</td>
<td>26</td>
<td>5/5</td>
<td>5h 19min</td>
<td>1000 m</td>
<td>feature intensive, many peaks above threshold</td>
<td>within 2/3 of mission</td>
</tr>
<tr>
<td>2008-06-26</td>
<td>0.52</td>
<td>54</td>
<td>5/5</td>
<td>4h 35min</td>
<td>1000 m</td>
<td>feature intensive, two high peaks along with others slightly above the threshold</td>
<td>within 1/2 of mission</td>
</tr>
<tr>
<td>2008-11-10</td>
<td>0.45</td>
<td>39</td>
<td>5/5</td>
<td>6h 40min</td>
<td>700 m</td>
<td>feature intensive, concentrated within first 2/3 of mission</td>
<td>within 1/3 of mission</td>
</tr>
<tr>
<td>2009-11-04</td>
<td>0.45</td>
<td>6</td>
<td>2/5</td>
<td>7h 00min</td>
<td>1000 m</td>
<td>poor INL, concentrated within first 1/5 of mission</td>
<td>within 1/7 of mission</td>
</tr>
<tr>
<td>2009-11-09</td>
<td>0.45</td>
<td>14</td>
<td>5/5</td>
<td>5h 17min</td>
<td>1000 m</td>
<td>feature intensive, several peaks slightly above threshold and homogeneously distributed</td>
<td>homogeneous</td>
</tr>
<tr>
<td>2009-11-10</td>
<td>0.45</td>
<td>13</td>
<td>3/5</td>
<td>1h 57min</td>
<td>1000 m</td>
<td>feature intensive, several peaks slightly above threshold and homogeneously distributed</td>
<td>homogeneous</td>
</tr>
<tr>
<td>2009-11-13</td>
<td>0.68</td>
<td>13</td>
<td>5/5</td>
<td>7h 11min</td>
<td>1000 m</td>
<td>feature intensive, one peak at the beginning, most peaks at the end, small peaks in the middle</td>
<td>homogeneous</td>
</tr>
<tr>
<td>2009-12-08</td>
<td>0.45</td>
<td>12</td>
<td>3/5</td>
<td>2h 36min</td>
<td>1000 m</td>
<td>poor, peaks slightly above the threshold within first 1/2</td>
<td>within 1/2 of mission</td>
</tr>
<tr>
<td>2010-03-23</td>
<td>0.45</td>
<td>3</td>
<td>2/5</td>
<td>6h 43min</td>
<td>1000 m</td>
<td>poor, only one peak at the beginning with another toward the end</td>
<td>at the beginning and the end</td>
</tr>
<tr>
<td>2010-07-01</td>
<td>0.21</td>
<td>1</td>
<td>2/10</td>
<td>6h 02min</td>
<td>2500 m</td>
<td>poor, none to weak feature signal except for two peaks towards the end</td>
<td>—</td>
</tr>
</tbody>
</table>

This article has been accepted for inclusion in a future issue of this journal. Content is final as presented, with the exception of pagination.
Simulation Results: 24 reward function profiles combinations improve $cv_Y$ and 12 $cv_p$. None improves $cv_A$, but four combinations improve the other two metrics. In this context, the use of $f_{ratio}$ has no impact.

Fig. 9 shows utilities based on $f_{dist}$ #1 and $f_{samplers}$ #8 for mission 2009-11-09, where all the samplers were utilized. The feature was homogeneously distributed, with 14 hotspots that were only slightly above the triggering threshold. Therefore, the use in isolation of any $f_{samplers}$ reward function results in less than five samples taken. But if we use $f_{samplers}$ in combination with $f_{ratio}$, we are able to take five samples in hotspots where all the metrics largely improve the nonutility original mission ones.

Table II shows absolute values for various metrics. However, these provide only a facet of how well a certain combination of reward functions performs for a given mission. First, as noted in Section V, the $[\min, \max]$ range of a metric depends on the actual spatial distribution of hotspots within the field. Second, metric values within the $[\min, \max]$ interval are not equally distributed as shown in Fig. 10 and also depend on the spatial spread of hotspots.

Some measure of an a posteriori comparison gives us an idea of how well our metrics behave. Let $H$ be the set of all the hotspots found in a given mission, $M$ the number of samplers, and $C$ the set containing all the combinations of $M$ elements of $H$. $C$ represents all the possible sample sets. Let $C_i \in C$ be a member of $C$ and let $cv(C_i)$ be the value of one of the metrics for the sample set $C_i$. Similarly, if $G \in C$ is the set of $M$ samples taken using a certain reward function selection, $cv(G)$ will be its metric value. One way to assess how $cv(G)$ performs against any other $cv(C_i)$ is by the use of a percentile analysis for $cv$ values. This tells us how many $C_i$ have worse metric values than $G$.

As an example, Fig. 10 represents all possible values for $cv_Y$ associated with all combinations of samples that can be formed with the 54 hotspots found in mission 2008-06-26. Similarly, Fig. 11 shows all $cv_A$ values for the 14 hotspots detected in mission 2009-11-09. Vertical lines show where the nonutility and reward function values lie. In both figures, the distribution is biased toward a qualitatively better metric to the left of the lines.

Table III shows the percentile (the larger the better) for both the nominal and utility-based approaches for all the three metrics. For example, the value of 13 for $cv_Y$ for the original nonutility-based approach in mission 2008-05-12 implies that $cv_Y(G)$ is better than only 13% of the possible $cv(C_i)$ values,
where $G$ is the set of samples taken by the nominal, nonutility-based, approach. Conversely, the utility-based approach yields better values for $c_{5\%}(G)$ than 71% of all possible sample sets.

As the table shows, in many cases, the reward functions exceed the nominal approach performance and also get good percentile values. No values are given for the last two missions as there were less than five hotspots in the field. In four missions, the results of both approaches are unsatisfactory. In three missions, not all the samplers were triggered, even if there were more than five hotspots. Two of these missions were cut short due to technical problems with the AUV, and since a premature end cannot be predicted by $f_{\text{ratio}}$, it is not able to reduce the threshold to exhaust all the samplers. In the case of 2009-11-04, the FOI was poor and concentrated within the first 1/5th of the field. A maximum of three samples can be taken in this volume given spatial constraints. Note, however, that no INL was found in the remaining 4/5th of the mission, so despite the reward functions used, the AUV returned with two unused samplers. In the case of mission 2008-11-10, there was a high number of hotspots, but their magnitude was only slightly above the threshold. Most of them were also concentrated in the first half of the mission. In this case, using any $f_{\text{samples}}$ results in some samplers not being utilized, which cannot be compensated by $f_{\text{ratio}}$ as it only actuates after almost half of the mission. Conversely, not using $f_{\text{samples}}$ results in all samplers being utilized.
Fig. 10. A histogram showing the distribution of \( c_{V} \) values for all the possible five-sample sets in mission 2008-06-26. To build the histogram, 1000 equally spaced categories have been created in the interval \([\min(c_{V}), \max(c_{V})]\), represented by \( X \)-axis. \( Y \)-axis shows the number of sample sets in each category. Vertical lines represent where the original nonutility- and utility-based approaches lie. The bigger the area of the figure on the right of these lines, the more sample sets have worse \( c_{V} \) value than the set resulting from our previous work or the utility-based approach, respectively.

Fig. 11. A histogram showing the distribution of \( c_{V} \) values for all the possible five-sample sets for mission 2009-11-09. Naively, the total number of elements is 2002. To build the histogram, 1000 equally spaced categories have been created in the interval \([\min(c_{V}), \max(c_{V})]\), represented by \( X \)-axis. \( Y \)-axis shows the number of sample sets in each category. Vertical lines represent where the original nonutility- and utility-based approaches lie. The bigger the area of the figure on the right of these lines, the more sample sets have worse \( c_{V} \) value than the set resulting from our previous work or the utility-based approach, respectively.

An earlier activation of \( f_{act,\ell} \) would be a possible solution for this kind of missions.

Table IV further summarizes results obtained from Table II, indicating the number of times using a given profile results in the best value of the metric. While the data sets are not statistically expansive, we do have some preliminary lessons learned from these experiments. As the table shows, profile #2 gives the best results overall for two of the three metrics; therefore, if no feature aware strategies are implemented it should be the default choice. Performance for profile #4 is quite close to that of profile #2, so it is also a good choice. Profile #4 is slightly more restrictive than profile #2, so it should be used when there is a strong indication of dispersed hotspots. In addition, profile #4 prevents taking samples unless at least half of the imposed distance constraint is met, so it is especially useful when the field is rich and hotspots are quite close to one another. Profile #1 performs better than profile #2 when spatial coverage \( (c_{V}) \) is

<table>
<thead>
<tr>
<th>Mission</th>
<th># of hotspots</th>
<th># of sample sets</th>
<th>Metric</th>
<th>Percentile</th>
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<tr>
<td></td>
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<td>Previous Approach</td>
<td>Reward Function</td>
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<td>2008-05-12</td>
<td>26</td>
<td>65,780</td>
<td>( c_{V} )</td>
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<td></td>
<td></td>
<td></td>
<td>( c_{V_A} )</td>
<td>68</td>
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<tr>
<td></td>
<td></td>
<td></td>
<td>( c_{V_B} )</td>
<td>52</td>
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<td>2008-06-26</td>
<td>54</td>
<td>3,162,510</td>
<td>( c_{V} )</td>
<td>42</td>
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<tr>
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<td>( c_{V_A} )</td>
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<td>( c_{V_B} )</td>
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<td>575,757</td>
<td>( c_{V} )</td>
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<td></td>
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<td>( c_{V_B} )</td>
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<td>2009-11-04</td>
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<td>6</td>
<td>( c_{V} )</td>
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<td>( c_{V_A} )</td>
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<td>( c_{V_B} )</td>
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<td>2,002</td>
<td>( c_{V} )</td>
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<td>( c_{V_A} )</td>
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<td>( c_{V_B} )</td>
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<tr>
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<td>1,287</td>
<td>( c_{V} )</td>
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<td>( c_{V_B} )</td>
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<td>( c_{V_A} )</td>
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<td>( c_{V_B} )</td>
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<td>( c_{V_A} )</td>
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<td></td>
<td>( c_{V_B} )</td>
<td>0</td>
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<td>2010-03-23</td>
<td>3</td>
<td>1</td>
<td>( c_{V} )</td>
<td>-</td>
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<tr>
<td></td>
<td></td>
<td></td>
<td>( c_{V_A} )</td>
<td>-</td>
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<td>( c_{V_B} )</td>
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<td>1</td>
<td>1</td>
<td>( c_{V} )</td>
<td>-</td>
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<tr>
<td></td>
<td></td>
<td></td>
<td>( c_{V_A} )</td>
<td>-</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>( c_{V_B} )</td>
<td>-</td>
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</tbody>
</table>

Table IV further summarizes results obtained from Table II, indicating the number of times using a utility function profile results in the best combination also highlighted in bold in that table.

<table>
<thead>
<tr>
<th>Metric</th>
<th>( f_{\text{distance}} )</th>
<th>( f_{\text{samplers}} )</th>
</tr>
</thead>
<tbody>
<tr>
<td>( c_{V} )</td>
<td>4 6 5</td>
<td>1 3 2 3 4</td>
</tr>
<tr>
<td>( c_{V_A} )</td>
<td>6 5 4</td>
<td>0 2 2 3 7</td>
</tr>
<tr>
<td>( c_{V_B} )</td>
<td>5 6 6</td>
<td>0 4 2 2 5</td>
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</table>
Fig. 12. Variation of the number of found hotspots with respect to the sampling threshold $T_f$, for the ten missions. The vertical line represents the actual threshold chosen for each mission. (a) 2008-05-12. (b) 2008-06-26. (c) 2008-11-10. (d) 2009-11-04. (e) 2009-11-09. (f) 2009-11-10. (g) 2009-11-13. (h) 2009-12-08. (i) 2010-03-23. (j) 2010-07-01.

a factor, but for the remainder two metrics its use does not yield appreciably better results. Therefore, profile #1 is relevant when spatial coverage is to be factored in.

In the case of sampler functions, not using any appears appropriate. This is especially true in missions with low feature signal or with high triggering threshold. In feature-rich situations, profile #8 performs quite well.

Except for $CV_{10}$ in 2009-11-13, using $f_{ran,0}$ gives better or equivalent results for all the metrics than not using it. In that mission, except for a peak at the beginning, the feature is concentrated toward the end of the mission. Use of $f_{ran,0}$ produces a sample to be taken in a small peak in the middle of the mission, wasting one sampler that could have been more useful toward the end. Therefore, unless the feature is expected to be concen-
Fig. 13. Variation of the reward function percentiles for the three metrics when the threshold is reduced down by 25% in steps of 5%, for 2009-11-09 mission. No hotspots are found when the threshold is increased. X-axis represents the threshold changes in percentage. Y-axis shows the percentiles. Values for $r = 0$ are those of Table III.

One shortcoming of our approach is the need to establish a triggering threshold before the mission. The lower the threshold, the more local maxima will be considered as hotspots, thereby increasing possible locations for sampling. Fig. 12 shows the variations in the number of hotspots for all the ten missions when the threshold is increased by 0.01 steps in the interval $[0.01, 0.99]$. In all cases, hotspots found within a 60-s temporal window are grouped together and considered to represent the same hotspot (the AUV ground speed is about 1.36 m/s, the distance is less than 90 m, and therefore, not significant for capturing biological diversity). As the figure shows, number of hotspots increases almost exponentially as the threshold is lowered. Even a small reduction on the triggering threshold increases the number of hotspots in almost all missions.

From the figure, one can distinguish two types of missions: those where the number of hotspots vary smoothly and those which are piecewise linear. If we compare Fig. 12 with Tables II and III, we can see that our approach behaves better in missions where the number of hotspots varies without many granular steps. This is also the case for missions where the threshold is not set high; so not only are several hotspots found, but also a small threshold increase assures a wide range of locations to sample, leaving the combined work of $f_{\text{samplers}}$ and $f_{\text{ratio}}$ to provide for desired spatial coverage.

To evaluate the robustness of our approach we have repeated the calculations shown in Table III for ten different thresholds, resulting from altering the original threshold in steps of 5% in the interval $[-25\%, 25\%]$. Reductions over 25% are known to generate hotspots with a very low value of $y_s$. In reality, for seven out of the ten missions a 10% increase yields no hotspots. As an example, Fig. 13 shows the variations of percentiles for the three metrics for mission 2009-11-09. $cv_\mu$ percentiles are the most stable, with little dependence on the threshold. Conversely, the values for $cv_\lambda$ change substantially as the threshold is reduced. There are two reasons for this: for low thresholds the poor spatial coverage is due to an early utilization of samplers, which cannot be compensated by $f_{\text{samplers}}$. A more steep profile, as in profile #9, would probably improve the performance. For thresholds closer to the original, most hotspots discovered have values only slightly higher than the threshold. As noted previously for 2008-11-10, not using $f_{\text{samplers}}$ quickly uses up the samplers, while using it results in empty samplers returned. An earlier activation of $f_{\text{ratio}}$, for example, automatically driven by the values of the hotspots found, would solve the problem.

B. Triggering Threshold Sensitivity Analysis

One shortcoming of our approach is the need to establish a triggering threshold before the mission. The lower the threshold, the more local maxima will be considered as hotspots, thereby increasing possible locations for sampling.

Fig. 12 shows the variations in the number of hotspots for all the ten missions when the threshold is increased by 0.01 steps in the interval $[0.01, 0.99]$. In all cases, hotspots found within a 60-s temporal window are grouped together and considered to represent the same hotspot (the AUV ground speed is about 1.36 m/s, the distance is less than 90 m, and therefore, not significant for capturing biological diversity). As the figure shows, number of hotspots increases almost exponentially as the threshold is lowered. Even a small reduction on the triggering threshold increases the number of hotspots in almost all missions.

We present a utility-based technique for discrete adaptive sampling. The principal aim is to integrate available information including science and operational constraints to decide where a set of samples can be taken. To do so, a utility is computed based on an a priori knowledge and presumed scientific intent; our current work deals with weakly informed and mission aware strategies with the expectation of inclusion of feature aware strategies in the future using the existing framework. The utility-based approach is especially useful in sequential sampling; new information obtained with previous samples can be integrated to acquire further samples. We show how the approach compares against a previously published technique using historical AUV data. The target application is in sampling INLs; however, the techniques are general and can be applied to sample most oceanic scalar fields when no an a priori model of the feature is available.

We also provide guidance on the appropriate choice of optimization metrics depending on scientific preference for spatial coverage, hotspot capture, or a mix between the two. Experimental results have shown that, even with weakly informed utility functions, our approach performs better using all the three metrics in comparison to the approach suggested in [30].
This initial effort in sampling has been promising and is likely to lead our work in a number of different directions. First, we plan to investigate the synthesis of utility functions applying machine learning techniques to historical data; using clustering techniques for mission classification as a means to learn suitable utilities as reward functions is one approach. The idea behind this is to explore whether there are “typical” mission types: with the FOI concentrated at the beginning/end, patchy, with many/few hotspots, etc. The scientist could have a general idea of what kind of feature distribution to expect, so the parameterization of functions could be automated. This will require more historical data than what is currently available, both for clustering and for the automatic selection of parameters for each cluster.

The long term goal is to experiment with feature aware strategies where some a priori knowledge of the field is available. We plan to build a probabilistic model of the feature of interest as the AUV makes in situ measurements. One approach is by using GPR [19] or kriging as used in spatial statistics. This allows us to estimate the signal and its uncertainty at unobserved points, and the utility can be altered depending on their proximity to high-value sample points. Such a model could also be used to predict peaks of the feature of interest [9]. Given the temporal variability of oceanic features even in very short time periods, the accuracy of such models for oceanographic phenomena needs study, especially for those learned offline. Also, using such models, decorrelation scales of features of interest from past data can be learned. From the models we can obtain a kernel function or variogram that defines the spatial variability of the data. This can directly be used as an utility function.

A model of the field can also potentially be available using synthetic ocean models such as [46]; however, the inclusion of dynamic features to be modeled within such systems is still tentative since there is poor to little understanding of such coastal features. Limited skill at the mesoscale in of itself poses a substantial challenge in the use of such techniques.

A more empirical approach to incorporate feature awareness is to potentially observe the survey area rapidly with the AUV and in the process build an approximate “map” of the field. This allows in situ inference to determine the overall characteristics of the survey area and having the vehicle revisit the vicinity of those locations that have FOI peaks. Having a map of the feature of interest will allow planning ahead for possible observations with better information. However, this approach is strongly dependent on the rates of feature evolution and the survey volume. In a large survey, returning back to location(s) of potential interest, which may be impacted by tides, might not be scientifically interesting. Surveys could also be augmented with shoreside support from a skilled oceanographer guiding the AUV with targeted commands with support from remote sensing data or other synoptic views of the coastal ocean. Our efforts to date are focused more on the latter as a means to augment onboard situational awareness on the AUV [10]. Finally, having an a priori estimation of a FOI by any of the former techniques will also allow in situ estimation of the quality metrics to be included in utility metrics.

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