Adaptive Informative Sampling with Autonomous Underwater Vehicles: Acoustic versus Surface Communications

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Abstract—Autonomous underwater vehicles (AUVs) are cost- and time-effective platforms for mapping and monitoring of aquatic environments. Previous works have shown the benefits of using informative adaptive sampling approaches for field estimation over running standard surveys. We are interested in extending these works into decentralized multi-robot approaches. Simulation experiments with two AUVs, comparing no data sharing with timed surfacing for data sharing, show that the system performs better when data is shared. We further explore the trade-off between using high-bandwidth surface Wi-Fi communications, at the cost of surfacing, and low-bandwidth underwater acoustic communications (acomms). Our simulation results show that for multi-vehicle decentralized adaptive sampling, we can increase modeling performance by having vehicles share their measurements. Furthermore, zero loss acomms can perform better than data sharing through timed surfacing events. However, when acomms throughput is reduced, modeling uncertainty increases.

I. INTRODUCTION

Autonomous underwater vehicles (AUVs) are cost- and time-effective platforms for mapping and monitoring of aquatic environments. They are used by biologists and oceanographers worldwide for sampling lakes and oceans, to obtain data for models of the environmental phenomena that they are interested in. For example, AUVs can be used to create data slices of the water column, both vertically and horizontally, of for example temperature, salinity or fluorescence responses. We are interested in collecting data to enhance the understanding of algae blooms. Algae presence is typically measured using Chlorophyll sensors or fluorometers. While AUVs with biological sensors provide ways of cheap data collection, the vehicles themselves are still relatively costly for most biology and oceanography groups. We envision a scenario where one or two groups of biologists or oceanographers come together for monitoring a lake, bringing their autonomous vehicles with biological sensors. To this end, our approaches are aimed at small groups of (small) AUVs.

Commercial off-the-shelf systems often come with software for running waypoints or lawn-mower surveys. These methods, however, may not guarantee that the end-user gets the most informative data within the time limits of vehicle endurance. Therefore, we are interested in informative adaptive sampling; i.e. adapting the vehicle trajectory online based on sampled data, while incorporating information-theoretic metrics to seek out the most informative sampling locations.

A. Related Work

Single-robot informative sampling approaches have been pioneered by [1, 2, 3]. In all cases, environmental phenomena are modeled using Gaussian Process (GP) regression [4]. GP regression is a common technique for modeling spatial uncertainty, known in geostatistics as Kriging. An information-theoretic criterion is used on the GP, such as mutual information [1, 2] or maximum posterior entropy [3], in combination with a path planning approach, to determine where to sample next. Singh et al. [2] looked at creating environmental models using GPs with mutual information, and used a path planning approach based on the recursive greedy algorithm [5].

When path planning happens during execution, incorporating new data, this is called adaptive sampling [3]. Low [3] ran adaptive sampling using log-Gaussian Processes (tGPs) and posterior map entropy, in combination with dynamic programming approaches for path planning. Note that log-Gaussian Processes [3] are used, because measurements of biological phenomena with hotspots, e.g. Chlorophyll in lakes and oceans, often follow a log-normal distribution [6]. In other words, the logarithm of measurement values follows a Gaussian distribution. We use similar approaches for environmental modeling and information-theoretic selection of sampling locations, to efficiently generate informative models.

Multi-robot approaches have been explored to some extent; planning paths for vehicles sequentially [2], running vehicles in geographically separate regions [7, 8], or running vehicles in parallel or one after another [3]. In sequential allocation, the same algorithm is run sequentially over all robots [2]. Paths are planned centrally and offline, before the robots are deployed. Some of the downsides of centralized planning include having a single point of failure, and communication overhead due to sharing of measurements and plans. Recent works by Low et al. and Ouyang et al. [9, 10] explored decentralized adaptive sampling with local planning. Vehicles broadcast measurements, as well as the chosen sampling location or the adjacency information. Coordination was done locally only, for robots with intersections in their planning neighborhoods. A disadvantage of local planning and local coordination is the susceptibility to suboptimal solutions.

Note that we focus on field estimation, while there are other related works regarding decentralized information gathering that concern themselves primarily with target search [11, 12]. We also differentiate ourselves from approaches where the sensors on the vehicle are non-myopic, e.g. [13, 14]; i.e. when
there is a significant sensor range, and the robot can observe different parts of the environment beyond its own location. Any sensors used for our approaches are myopic sensors that take point measurements; hence we cannot observe beyond the current vehicle position. This means that the robot has to visit every possible location in a sample space, in order to get measurements for it. Finally, while some works focus on the specific modeling approach or path-planning methods, such as [14], we focus on multi-robot coordination approaches.

We are interested in developing informative sampling approaches for multi-AUV systems, with fully decentralized planning and coordination. Our system is designed to allow vehicles to plan independently over the whole survey area, and to coordinate often, with minimal communication overhead.

B. Problem Outline

We investigate how increased coordination through data sharing can increase modeling performance. For this paper, our main focus is comparing the environmental modeling performance for multi-AUV informative adaptive sampling, while sharing data through two methods of communication:

1) the AUVs interrupt their at-depth survey to come to the surface and share all measurements taken so far,
2) the AUVs attempt to share measurements (semi-) continuously during at-depth surveys, using acoustic underwater communications (acomms).

The AUVs will be able to share fewer measurements when using acomms, but will not have to spend any time on surfacing actions. Given that acomms are often lossy [15], we also look at the scenario where throughput is reduced, e.g., only 70% or 50% of the messages get through. In these cases, we see that although the model’s predictive mean performance reduces only slightly, the model uncertainty can increase significantly.

II. METHOD

Our adaptive informative sampling approach consists of the following components: On each vehicle, we first use GP regression to create a model of the environment from measurements taken. Then we use a greedy path planning approach which, based on the posterior map entropy of the model that is being built, decides where the vehicle should sample next. Finally, we investigate how sharing data between multiple vehicles can improve the system performance. For all experiments, we evaluate modeling performance based on average performance across simulations.

A. Gaussian Process regression

A common method for creating environmental models of sampled spatial data is Gaussian Process (GP) regression [2, 3, 4]. The GP is specified by a mean function and covariance matrix (i.e. kernel), for which we use the standard approach of taking a zero-mean prior and an isotropic squared exponential covariance function [4]. In this work, we use log-Gaussian Processes (logGPs) [3], which are used when the data better fits a log-normal distribution, as is often the case for biological data [6]. The GP is a non-parametric model, but has hyperparameters that are typically estimated using gradient-based optimization [4]. We use resilient backpropagation [16], and run a pilot survey for initial hyperparameter optimization.

Formally, let \( Y_x \) denote an \( \ell \)GP modeling the sensor value \( y_x \) at location \( x \in \mathcal{X} \), where \( \mathcal{X} \subseteq \mathbb{R}^2 \), i.e., we sample in the plane. Let \( Z_x = \log_{e} y_x \). The GP’s posterior mean and variance, \( \mu_{Z_x|d_n} \) and \( \sigma_{Z_x|d_n}^2 \) (for posterior data \( d_n \)), are then used to calculate the posterior mean and variance for the \( \ell \)GP [3]:

\[
\mu_{Y_x|d_n} = \exp\{\mu_{Z_x|d_n} + \frac{\sigma_{Z_x|d_n}^2}{2}\} \\
\sigma_{Y_x|d_n}^2 = \mu_{Y_x|d_n}^2 \left( \exp\{\sigma_{Z_x|d_n}^2\} - 1 \right)
\]

This posterior mean and variance represent the model’s estimation of the data value, and the uncertainty in this estimate.

We use the maximum posterior entropy criterion on our created \( \ell \)GP to find the next waypoint. As derived in [3], this can be expressed in terms of the GP posterior mean and variance:

\[
H[Y_{x_{i+1}}|d_i] = \log \sqrt{2\pi e \sigma_{Z_{x_{i+1}}|d_i}^2} + \mu_{Z_{x_{i+1}}|d_i}
\]

where \( d_i \) is the already sampled data. We take a greedy approach to path planning, choosing for the next waypoint the
location with globally highest maximum posterior entropy. The goal of the vehicle is thus to decrease variance (i.e. modeling uncertainty) at sample locations, as well as to visit locations with a high expected sensor value, as is clear from Equation 3.

B. Simulation set-up

We simulate up to two underwater vehicles, which run at 1.5 m/s, and at five meters depth while sampling. The vehicles are simulated using the MOOS-IvP middleware [17], which includes a simple simulation of vehicle dynamics and PID control. MOOS-IvP enables behavior-based autonomy, and we use the following standard behaviors for our mission: waypoint, loiter, constant depth, and (inter-vehicle) collision avoidance [17]. Each vehicle independently samples data, creates a GP model, and runs path planning to decide where to go next. Thereby we keep the adaptive sampling approach completely decentralized.

In order to simulate the biological data, we create a 3-D grid of data (400x200x15 m, see Figure 1) that incorporates two 3-D Gaussians and additive Gaussian noise, to simulate (an area in) a lake with algae blooms. We sample in the horizontal plane, at a certain depth, and make a 2-D GP model. The grid space is over a pre-specified area of interest, with 10 m spacing for the longitude and latitude axes, and 0.5 m spacing for the depth axis. The noise amplitude on the simulated data is 20 percent of the data value amplitude. This data value amplitude is set to 40, as a proxy for high Chlorophyll \( \mu g/ L \) values. Note that the data value distribution for this field will follow a log-normal distribution. We run our simulations on this one simulated field only, such that we can directly compare models and their performance between the different set-ups.

Figure 2 shows an example horizontal slice from the simulated data, at five meters depth. To simulate a sensor, the AUV retrieves the closest (Euclidean distance) data point from the simulated grid, and we add Gaussian noise (\( \sigma = 1.5 \)) to model sensor noise. Data is sampled at a frequency of 1 Hz.

To estimate the hyperparameters for the GP, we run a pilot survey on the AUV before every experiment. This survey is a coarse lawnmower (100 m track spacing), run horizontal and vertical over the survey area. When run by two vehicles, the area is split vertically, and each vehicle runs the pilot survey over one half (200x200 m). For multi-vehicle parallel and timed data sharing approaches, the data measurements are shared after the pilot, for acomms approaches measurements are shared continuously during the pilot survey.

C. Simulated communications

As mentioned in the previous section, each vehicle independently models the environment with a GP and runs greedy path planning. There are no central components to the system. For multi-vehicle coordination, we consider at this point only data sharing approaches. We are interested in comparing multi-vehicle performance between when the vehicles have limited, but (semi-) continuous, underwater communication, versus when the vehicles can communicate fully, but need to surface.

To simulate underwater acoustic communications, we use the Goby acomms suite [18], with a TDMA (Time Division Multiple Access) scheme. The TDMA scheme is set up such that each vehicle has a three second time slot in which it can send 32-byte messages. Given the simulated acoustic modem processes and acomms protocols, this means that each vehicle can send 1-2 messages per time slot. The underwater communication range is limited to 500 m. The acomms is always used by the vehicles to exchange vehicle positions for collision avoidance. For initial experiments, we assume that no messages are lost, i.e. obtain a throughput of approximately 100%. For the final two experiments, we probabilistically drop respectively 30% and 50% of the messages, i.e. obtain a throughput of approximately 70% and 50%.

When on the surface, we assume wireless communications for data sharing. This allows for much greater bandwidth and frequency of messaging compared to acomms. When vehicles surface, they can share data only after completing a successful handshake, to guarantee that both vehicles are on the surface and ready to share data.

For data sharing through acomms, the vehicles are unable to exchange all measurements, due to the limited bandwidth of acomms. Given the TDMA scheme, each vehicle can send on average two 32-byte messages every six seconds. To minimize the amount of messages, we merge data measurements into vehicle status messages, which are already sent for collision avoidance. Each message thus contains vehicle ID, position (x, y, depth, altitude), orientation (heading, pitch, roll), speed, and two data points (x, y, depth, data value). The data points contain their location, because the measurements may be older than the current vehicle position.

D. Experiments

In total, we have run simulations for adaptive sampling with two AUVs for six different scenarios:

- lawn mower survey,
- adaptive, parallel,
- adaptive, timed data sharing on surface,
- adaptive, continuous data sharing through acomms,
- adaptive, continuous data sharing through deteriorated acomms, at 70% throughput,
- as the previous item, at 50% throughput.

In order to determine the modeling performance of our multi-robot approach, we first compare a standard lawn mower survey with running adaptive sampling in parallel, and with running adaptive sampling with timed data sharing on the surface. The lawn mower survey is a high resolution (20 m track spacing) lawn mower, run both horizontally and vertically over the survey area. For the two vehicle scenario, the area is split vertically, with one vehicle covering the west, and the other vehicle covering the east part. The duration of running the lawn mower survey is used as the mission duration for the adaptive surveys.

In the adaptive sampling scenario, vehicles choose waypoints in the resolution of the data grid (10 m spacing), using Equation 3. For the parallel adaptive sampling case,
both vehicles run adaptive sampling, without sharing data or coordinating their actions. For the timed data sharing, the vehicles surface every 10 minutes, to exchange data. In both cases, the vehicles also share data after the pilot survey, and at the end of the whole survey, such that both vehicles should have all measurements at the end, for the best model.

Finally, we compare the timed data sharing approach, to acomms-based data sharing. The advantage of acomms is that the vehicles do not have to surface to be able to share their data. However, the communication channel is much more restricted, and therefore they cannot expect to be able to share all measurements. We test three different acomms scenarios: 100%, 70% and 50% throughput.

III. RESULTS

We compare the modeling performance between different types of mission set-ups using Root-Mean Squared Error (RMSE) and negative log-likelihood (NLL). The RMSE compares the predictive means from the ℓGP, created on each vehicle, to the simulated data model from which measurements are taken (with simulated sensor noise). The NLL takes into account not only the predictive mean, but also the predictive variance, while comparing to the simulated data model. Overall, we see increases in NLL because the incoming data measurements make the model deviate from its initial estimate, i.e. the state of the initial hyperparameter optimization. Typically, we do see a drop in NLL after the final hyperparameter optimization ($t = 12$ for single AUV, $t = 7$ for two AUV experiments). As mentioned in Section II-D, we end the adaptive sampling after the same amount of time has passed as it takes to do the high resolution lawnmower survey. Given that the last time step is after the final hyperparameter optimization, it typically shows a bigger change compared to the time steps before. Note that, typically, for a lawnmower survey one would not need to run a separate pilot for hyperparameter optimization, if one can wait until the end of the survey for the model. However, considering intermediate access to the model, robustness to vehicle failures, and to be able to do this time-based comparison, we run the same pilot survey before the lawnmower surveys with hyperparameter optimization.

A. Single AUV results; lawnmower vs. adaptive

Figure 3 shows the single AUV results, where we compare the ℓGP quality for ten simulations of lawnmower and adaptive surveys. Figure 3a shows the root mean squared error (RMSE) between the simulated data model and the vehicle’s ℓGP model. On the right, Figure 3b shows the negative log-likelihood (NLL) of the created ℓGP model. The NLL also incorporates posterior variances, whilst RMSE only evaluates posterior means.

We can see that running adaptive sampling instead of a standard lawnmower pattern consistently decreases the RMSE more quickly, and the negative log likelihood grows more slowly and is lower at any time. This confirms the result found in related works [2, 3], which showed the benefits of adaptive sampling over running standard lawnmower surveys. The quick reduction of RMSE for adaptive sampling suggests that the adaptive sampling survey could potentially finish earlier than the lawnmower survey.
(a) Root-Mean Squared Error (RMSE)

(b) Negative Log-Likelihood (NLL)

Fig. 4: RMSE and NLL averages of ten simulations for 2 AUVs running lawnmower and adaptive sampling surveys. Adaptive surveys are parallel, and timed data sharing. Error bars are omitted for readability.

Fig. 5: RMSE and NLL averages of ten simulations for 2 AUVs running adaptive sampling with either timed data sharing or acoustic communications. Error bars are omitted for readability.

B. Multiple AUVs; lawnmower vs. adaptive parallel vs. adaptive timed data sharing

For simulations with two AUVs, Figure 4 compares the simulation results of standard lawnmower surveys to two informative adaptive sampling approaches. RMSE and NLL of the GP are plotted against time. As in the single-vehicle experiments, we use time steps of 600 seconds, where the first result \( t = 1 \) is after initial hyperparameter optimization, and the last result \( t = 7 \) is after the final hyperparameter optimization. Considering the time steps for predictions made during the survey, i.e. \( t = 1 \) to 11 for single AUV and \( t = 1 \) to 6 for dual-AUV, it is clear that the whole survey takes only about half the time when running with two AUVs.

The results show that the model’s RMSE decreases more quickly when running either of the adaptive sampling approaches, and the NLL is continuously better. Note that, for the lawnmower survey, one of the AUVs (‘auv1’) performs significantly worse on RMSE, up until the final timestep where all data is shared. This is due to the fact that the survey area is split for two AUVs. Only one half contains the simulated
bloom, and therefore, without gathering more data in that area, the second AUV can not improve the model as much as the other. For adaptive sampling, we show simulation results of running two AUVs in parallel, and using timed data sharing (on the surface). The results clearly show the improvements of adaptive sampling over standard lawnmower surveys. The addition of timed data sharing further improves the modeling performance, i.e. both RMSE and NLL have decreased.

C. Multiple AUVs; timed data sharing vs. acoustic communications

Figure 5 compares the simulation results of two AUVs using timed data sharing (TDS) on the surface, with two AUVs continuously sharing data through acomms. As has been explained in Section II-B, the vehicles run their survey at 5 meters depth. Hence, this is also the vertical distance the TDS AUVs need to transit to the surface to be able to share data. As Figure 5a shows, the modeling performance given the RMSE is similar for the two approaches. Figure 5b shows that the modeling performance is better in terms of negative log-likelihood for the acomms approach. The good performance of acomms is most likely due to spatial correlation between measurements, such that subsampling the measurements still gives good results. Furthermore, because the AUVs do not have to interrupt the survey, they can spend more time improving the model.

D. Multiple AUVs; deteriorating acoustic communications

As explained in Sections I-A and II-D, we ran ten simulations for acomms with reduced message throughput, resp. 70 and 50%. Table I shows the average number of messages exchanged between the vehicles through acomms, for each throughput setting, as well as the empirical throughput.

![Graph showing RMSE and NLL averages of ten simulations for 2 AUVs running adaptive sampling with different throughput (100, 70, 50%) acoustic communications. Error bars are omitted for readability.](image)

**TABLE I**: Average number of messages received on each vehicle per simulation, and empirical percentage of messages received versus the full 100% throughput.

<table>
<thead>
<tr>
<th>Throughput setting</th>
<th>Avg msgs received</th>
<th>Empirical percentage</th>
</tr>
</thead>
<tbody>
<tr>
<td>100</td>
<td>2681</td>
<td>100</td>
</tr>
<tr>
<td>70</td>
<td>1883</td>
<td>70.2%</td>
</tr>
<tr>
<td>50</td>
<td>1336</td>
<td>49.8%</td>
</tr>
</tbody>
</table>

Figure 6 shows the RMSE and NLL for all acomms simulations. For the RMSE, we can see that performance, on average, decreases slightly with decreased throughput. For the NLL, we can see that most perform similarly, but for one of the AUVs the degradation increases a lot more with decreased throughput. We further discuss this result in the next Section, IV.

**IV. DISCUSSION & FUTURE WORKS**

In this work we explored how exchanging data between the sampling robots benefits environmental modeling with (log-) Gaussian Processes. We show that adaptive sampling outperforms standard survey methods. Furthermore, when running simulations with multiple vehicles, we see that increased sharing of measurements improves individual modeling performance. When vehicles share measurements through timed data sharing, they perform better than when running adaptive sampling in parallel, without sharing measurements.

We further explore the performance for timed data sharing on the surface, versus underwater acoustic communications (acomms). The benefits of surfacing are increased throughput and bandwidth, but there is a cost in terms of time spent on surfacing, data sharing, etc. Section III-C compared the modeling performance between timed data sharing and acoustic communication. While the modeling performance is similar...
in terms of RMSE, we see that the modeling performance in terms of negative log-likelihood is not as good for the timed data sharing. We hypothesize that this has two causes: For one, the timed surfacing for data sharing reduces the overall time available for sampling. In the end, the vehicles will have taken fewer measurements, and therefore there remains greater uncertainty in the created model. The second reason that timed data sharing is performing worse for NLL, may come from the fact that there is no coordination of vehicle actions. Every time the vehicles surface and share their data, they end up with approximately the same model. Without coordinating actions, they will thus try to go to the same areas for further sampling, until small differences in route and sensor noise introduce enough variation to lead to different sampling locations. This is somewhat mitigated in the acomms case because, even with 100\% throughput, not all measurements can be shared, and therefore the models are at all times slightly different. At the same time, with acomms, the AUVs do not synchronize their actions at any time, and therefore there will be more diversity in paths and sampling locations.

Finally, we compare the performance for acomms with different throughput levels; 100\%, 70\% and 50\%. Section III-D showed that modeling performance deteriorates with decreased acomms throughput. Figure 6 showed furthermore that performance decreases more for one of the vehicles than the other. This difference is likely due to the difference in measurements taken during the pilot survey. Currently, the area is split vertically for the pilot survey; one AUV runs the west half, while the other runs the east half. At the same time, the simulated algae bloom is in the west area. For the acomms simulations, data is shared only through acomms and not through surfacing events. Therefore, with loss of throughput, one of the AUVs will initially get fewer measurements inside the ‘hot spot’. The pilot data is kept after the pilot, and therefore the AUVs start out with slightly different models. Due to having different models, they will also sample in different locations, and one of the AUVs is thus running adaptive sampling on a model that is not as good.

A. Future works

To improve timed data sharing on the surface, it would be useful to coordinate actions between the vehicles. When sharing measurements through lossy acomms, we saw that one of the AUVs may have a less accurate model than the other. To avoid this, we can consider two approaches; either we can remove the pilot data from the GP, i.e. merely use the data for hyperparameter estimation, and start adaptive sampling from a blank slate. This however, seems like a waste of data. Another approach would be to have one surfaced data sharing event after the pilot, to make sure both vehicles have the same initial dataset. This is also in the interest of robustness, because we would like both vehicles to have as good a model as possible at all times, in case one of the vehicles would have problems.

B. Conclusions

Overall, we have demonstrated the benefits of data sharing between multiple vehicles that run decentralized adaptive sampling. Our simulations show that when using acoustic communications, modeling performance is superior to timed data sharing, when there is 100\% throughput. However, it is also clear that the performance, especially in terms of model uncertainty, deteriorates with reduced throughput. In future works, it would be interesting to investigate the effects of increased coordination on vehicle actions.

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