Multi-Robot Strategies for Adaptive Informative Sampling with Autonomous Underwater Vehicles

Stephanie Kemna   Gaurav S. Sukhatme

Multi-Robot Coordination through Dynamic Voronoi Partitioning for Informative Adaptive Sampling in Communication-Constrained Environments


Surfacing Strategies for Adaptive Informative Sampling with a Surface-based Data Hub


1. Build a model of the environment: Gaussian Processes
2. Use information-theoretic metric to find sampling locations: entropy
3. Run path planning over found locations: global greedy
When run online, in the field, in response to what the vehicle is sensing: adaptive informative sampling

Vehicles request surfacing events

Vehicles calculate everyone’s Voronoi partitions based on model
Simulation results:

Improvements in early stages of model creation, in particular for more complex scenario

Previous approach requires synchronized surfacing. Can we gain from adding a surface-based data hub allowing asynchronous surfacing?  Main question: when to surface?

Altruistic surfacing: how much do I have to share?

\[ 1.0 - \left( \frac{\sum \sigma_i^2}{\sum \sigma_{i-1}^2} \right) \geq \tau \]

Gain-based surfacing: how much can I obtain at the surface?

\[ (d_{i-1} f_s (n_{awus} - 1)) > 2(1 + (t_i / t_e))(f_s d_{os}) \]

Simulation results:

<table>
<thead>
<tr>
<th></th>
<th>no hub, timed</th>
<th>no hub, vor</th>
<th>with hub, timed</th>
<th>with hub, altruistic</th>
<th>with hub, gain-based</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>20.0 ± 0.06</td>
<td>14.7 ± 1.1</td>
<td>20.6 ± 2.9</td>
<td>6.4 ± 0.9</td>
<td>18.7 ± 1.1</td>
</tr>
</tbody>
</table>

Table 9.1: Average number of surfacing events, with one standard deviation, averaged over all scenarios, over both vehicles, over all 30 simulation runs.

<table>
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<th>with hub, gain-based</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>94.7 ± 189</td>
<td>88.7 ± 409</td>
<td>93.6 ± 293</td>
<td>10135 ± 366</td>
<td>9347 ± 298</td>
</tr>
</tbody>
</table>

Table 9.2: Average number of samples in final GP for hyperparameter optimization, with one standard deviation, averaged over all scenarios, over both vehicles, over all 30 simulation runs.

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</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>1309.9 ± 23.2</td>
<td>2103.3 ± 208.6</td>
<td>1209.5 ± 24.3</td>
<td>1369.8 ± 17.0</td>
<td>1278.5 ± 30.1</td>
</tr>
</tbody>
</table>

Table 9.3: Average time of first surfacing event with standard deviation, averaged over all scenarios, over both vehicles, over all 30 simulation runs.

Conclusions:

- all approaches perform approximately equal w.r.t. RMSE between vehicle-created models and the ground truth
- Voronoi coordination approach has wider variance on initial performance, but also better performance for scenarios sampled from GP
- Altruistic surfacing strategy outperforms gain-based: similar performance is obtained with far fewer surfacing events.