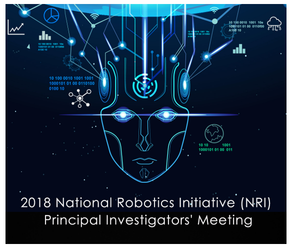
Co-Multi-Robotic Exploration in Communication Constrained Environments

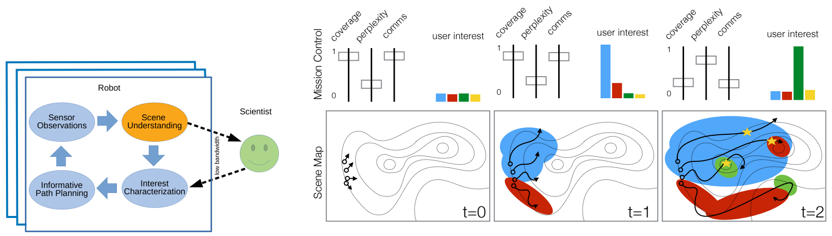
PIs: Yogesh Girdhar, Brian Claus, James Kinsey
{yogi, bclaus, jkinsey}@whoi.edu

WARPLab
warp.whoi.edu
Woods Hole Oceanographic Institution



Motivation:

This project aims to develop an approach to co-robotic exploration of unknown environments with a team of robots, to aid in the discovery and mapping of scientific phenomena, in extreme environments such as the deep sea where autonomous robots operate under strong communication bottlenecks. The proposed robotic approach aims to use a Bayesian nonparametric scene model to learn high level scene descriptors, which can then be used to for efficient robot-robot and human-robot communications.

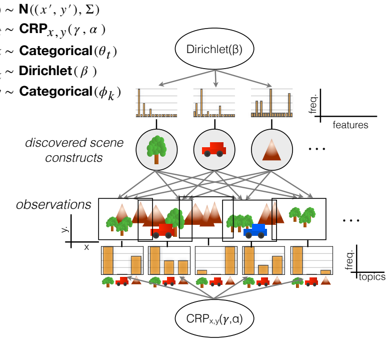


Example of a user interface for co-robotic exploration.

Scene Model:

The generative model for the observed data is described as following. At time t, we observe a discrete observation w at a noisy location (x, y), modeled as a random sample from a Gaussian centered around the true position (x', y'). We model the distribution of scene labels with a spatially correlated Chinese Restaurant Process (CRP), and the distribution of visual features describing each scene label with a Dirichlet distribution.

$$(x, y) \sim \mathbf{N}((x', y'), \Sigma)$$
$$\theta_t \sim \mathbf{CRP}_{x,y}(\gamma, \alpha)$$
$$k \sim \mathbf{Categorical}(\theta_t)$$
$$\phi_k \sim \mathbf{Dirichlet}(\beta)$$
$$w \sim \mathbf{Categorical}(\phi_k)$$



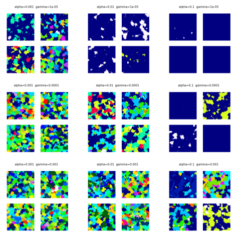
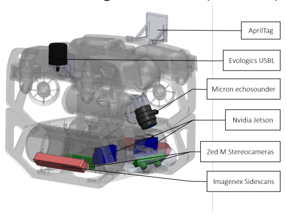
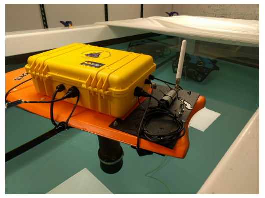


Figure on the left show random samples from the generative process describing the spatial distribution of scene labels using the spatially correlated CRP. The hyper parameters can be used to control the patchiness of the scene constructs, without explicitly learning a classifier.

Robot System:

The proposed co-robotic exploration system consists of an autonomous surface vehicle responsible for localizing the AUVs and acting as the communication relay; and one or more AUVs equipped with a multitude of sensors and on-board processing power to enable in-situ scene understanding. As shown in the figure below, (left) the AUV is equipped with bandwidth heavy sensors such as stereo cameras and side scan sonars, in addition to, an echosounder (altitude sensing), acoustic modem, and three computers, two of which have GPUs for computing scene maps in realtime. The topside vehicle (middle) has radios for communicating with the scientists, and a USBL array for acoustic communications and robot localization. Both the AUV and the ASV working together (right) enable the operation of the system even when the the AUV is outside the acoustic comms range of the topside operator.





Tank Trials:

We demonstrated the scene modeling approach in a controlled tank environment with an artificially constructed scene consisting of seaweed, stones, sand, grass, and a crab; and attempted to build a global scene map from the streamed data. The robot was localized using AprilTags and an external camera, mimicking the position information provided by the surface vehicle via GPS and USBL. The AUV was then instructed to follow a lawn-mower pattern in the tank. The downward facing stereo camera provided an RGB-labelled point cloud which were then streamed into the scene modeling system. Old data points are updated with new topic information even as new data points are processed using an online Gibbs sampler.

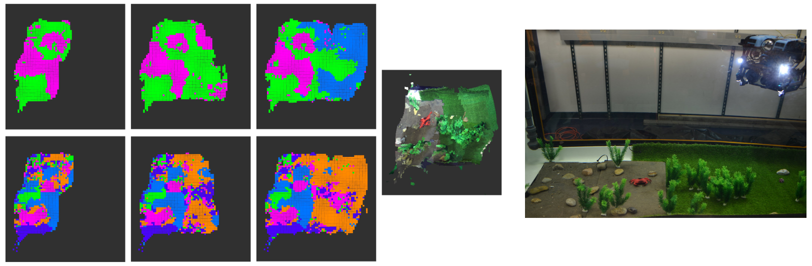


Figure above shows the progression of the scene map generated by the robot as it explores an artificially created scene in a test tank for two different sets of hyperparameters.

Simulated Coral Reef Exploration:

We evaluated the ability of the proposed scene modeling approach to characterize a coral reef environment, given the bandwidth constraints. We used the HAW-2016-48 dataset from the Scripps 100 Island Challenge project to simulate observations.

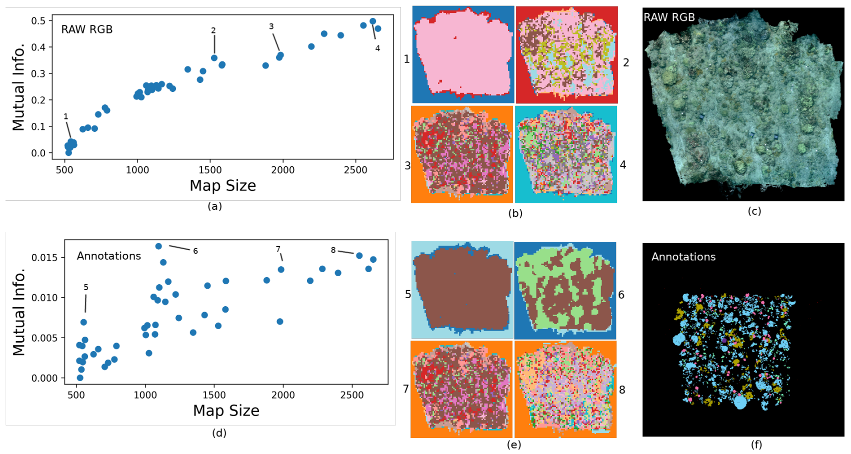
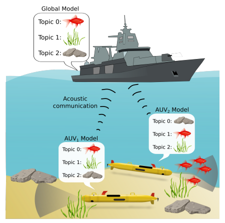
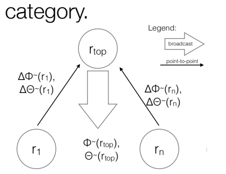


Figure above shows (a) Scatter plot evaluating different scene maps generated by varying hyperparameters *alpha, beta, gamma*, evaluated on Mutual Information Score with RGB photomosaic map (c) of the reef, and the size of the compressed map in bytes. (d) Scatter plot where the same maps are evaluated by their MI score with the expert annotations (f). MI score is only computed for the region of the reef for which there were annotations. (b,e) show examples of generated map along with their locations in the scatter plots. Variation in the colors of the scene map is purely random, as is only used to distinguish a region from other types of regions.

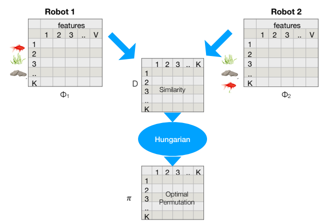
Distributed Scene Understanding Problem:

When multiple AUVs are exploring an environment, each individual robot builds its own local scene model. When IDs of these scene constructs (topics) are shared between robots and the topside operator, there there is no guarantee that the same IDs from different robots correspond to the same visual category.





The proposed approach merges the scene model at the topside central node using the Hungarian algorithm, at a rate permitted by the available bandwidth, and then the broadcasts the merged model back to every robot.



Define cost in terms of "topic distance"

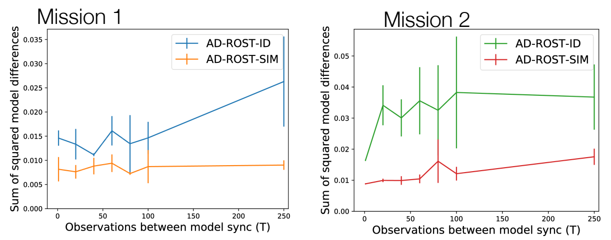
$$D(\hat{\phi}_{kw}, \hat{\phi}'_{kw}) = \sum_{k=1}^{K} \|\hat{\phi}_{kw} - \hat{\phi}'_{kw}\|^2$$

Solve for the optimal permutation with respect to the first vehicle

$$f(\pi(\hat{\phi}_{kwr})) = \sum_{k=1}^{K} \|\pi(\hat{\phi}_{kwr}) - \hat{\phi}_{kw1}\|^2$$

$$\pi_r^* = \arg\min_{\pi(\hat{\phi}_{kwr})} f(\pi(\hat{\phi}_{kwr}))$$

Experiments with simulated missions using real data suggest that merging scene models using the Hungarian algorithm works well even when the merges happen infrequently (low bandwidth), compared to trivial approach to merging of the models.



Future Directions:

- Field trials and demonstration in a coral reef environment.
- Peer-to-peer distributed scene understanding.
- Merging scene models with different numbers of scene constructs (CRPs).
- Use of nested Chinese Restaurant Process for hierarchical scene understanding.
- Multi modal scene models using acoustic and optical imagery.

Summary:

- Preliminary results demonstrate the feasibility of a co-robotic visual exploration of an unknown environment, even in the presence of strong bandwidth constraints.
- Use of a Bayesian nonparametric scene model enables in-situ learning of scene descriptors that can be used for communication over low bandwidth.
- Multiple exploring AUVs can learn a coherent scene models by occasionally syncing with the topside node.

References:

1. Doherty, K., Flaspohler, G., Roy, N. & Girdhar, Y. Approximate Distributed Spatiotemporal Topic Models for Multi-Robot Terrain Characterization. in Intelligent Robots and Systems (IROS) (2018).
2. [SUBMITTED] Girdhar, Y. et al. Enabling Co-Robotic Scientific Exploration of Unknown Environments over a Low Bandwidth Communication Channel. in IEEE International Conference on Robotics and Automation (2019).