VIRTUAL MAPS FOR AUTONOMOUS EXPLORATION OF CLUTTERED UNDERWATER ENVIRONMENTS

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INTRODUCTION

We present a novel exploration framework for underwater robots operating in cluttered environments, built upon simultaneous localization and mapping (SLAM) with imaging sonar. The proposed system comprises path generation, place recognition forecasting, belief propagation and utility evaluation using a **virtual map**, which estimates the uncertainty associated with map cells throughout a robot's workspace.

UNDERWATER SLAM USING SONAR

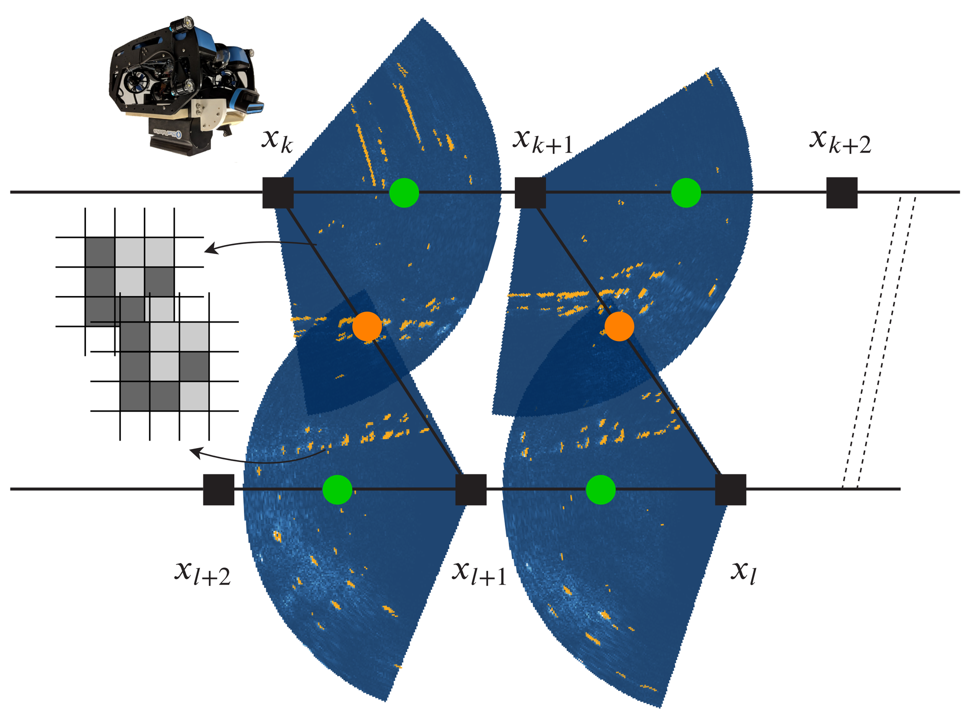

Figure 1: Our exploration framework is implemented in conjunction with an underwater SLAM framework for a sonar-equipped underwater robot (BlueROV2). It is built upon a keyframe-based factor graph comprised of pose variables at keyframes (black squares) and two types of factors: sequential factors (green circles) and loop closure factors (orange circles), derived from scan matching.

E-M EXPLORATION ALGORITHM

Exploration addresses the problem of building an accurate and complete map of an unknown environment by actively gathering measurements through planning. It requires good balance between information gain (which leads to faster coverage) and uncertainty reduction (which leads to accurate estimation). Our proposed exploration algorithm leverages the traditional Expectation-Maximization (E-M) method to address the problem. In the E-step, latent virtual landmarks are computed based on the current estimate of the trajectory and the history of measurements. In the M-step, a new trajectory is selected such that the expected value of joint probability, given the virtual landmark distributions, is maximized.

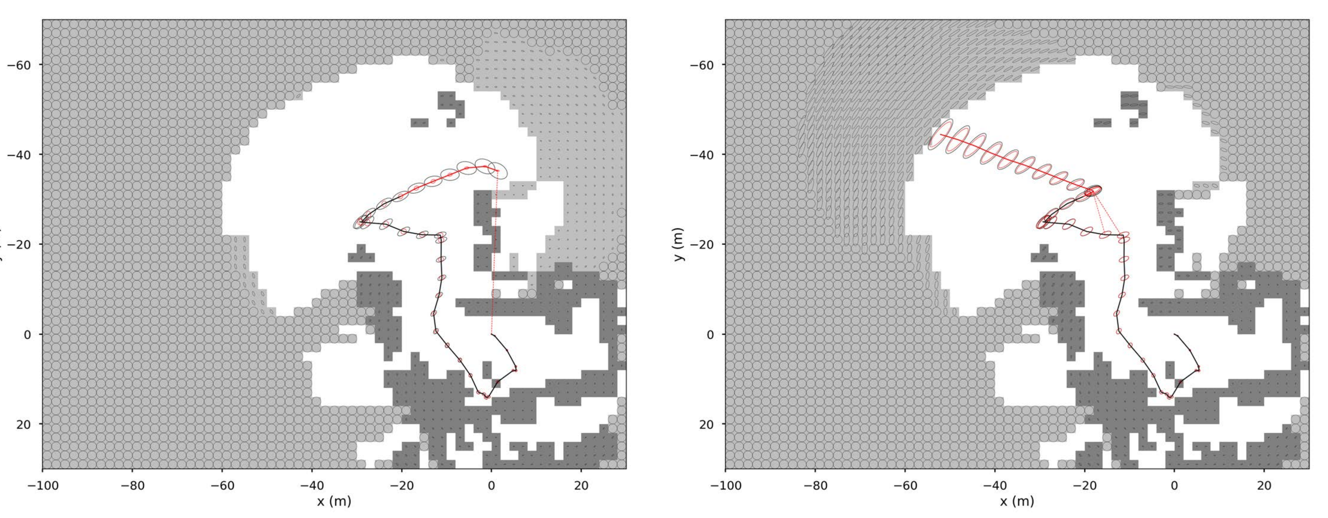

Figure 2: Planning over virtual maps, with two candidate trajectories shown. Virtual landmarks are maintained within the cells of a low-resolution occupancy map. The error covariances of all occupied and unknown cells are shown as ellipses drawn inside each respective map cell, along with anticipated loop closure constraints. The candidate trajectory on the left reduces the uncertainty of virtual landmarks as a result of a loop closure, whereas the trajectory on the right covers unknown space without significantly reducing map uncertainty.

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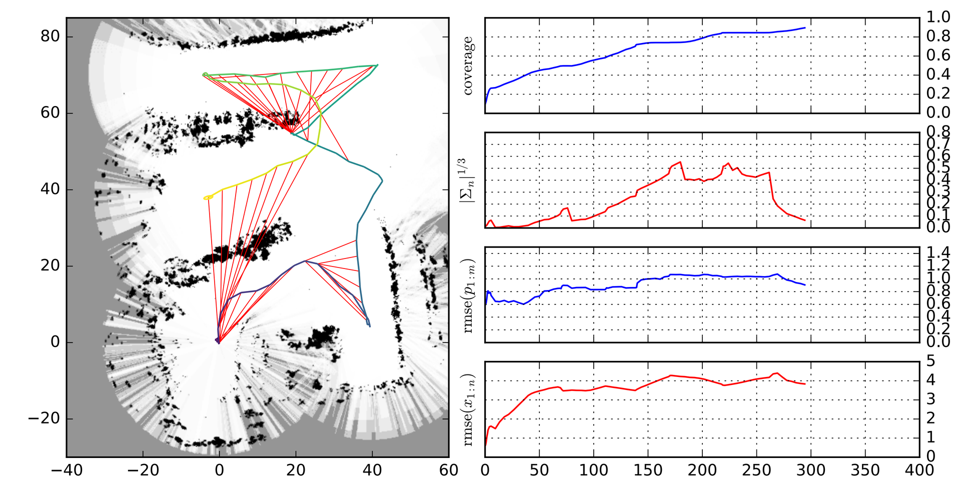
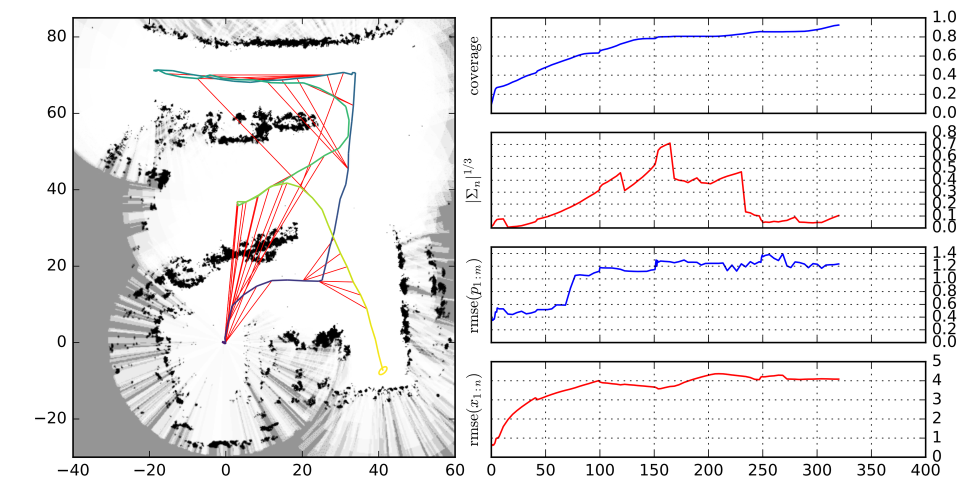
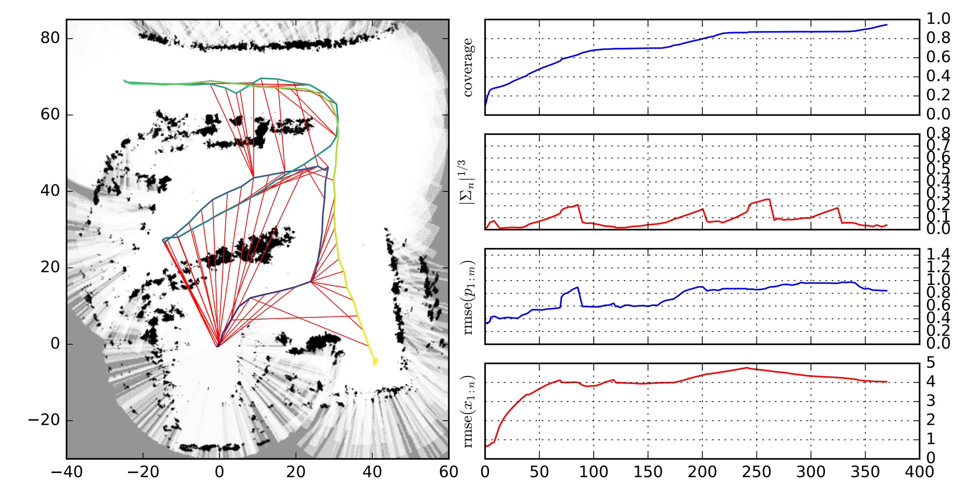
EXPLORATION IN SIMULATED ENVIRONMENTS USING POSE-SLAM



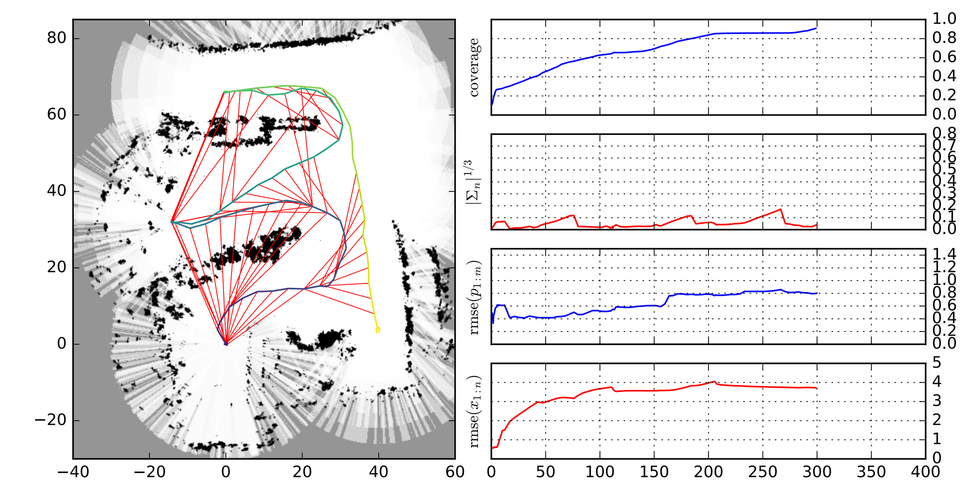
(a) Example of **frontier-based** exploration, which explores by repeatedly driving to the *nearest frontier* (NF) goal defined at the boundary between unknown and obstacle-free space.



(b) Example of **next-best-view** (NBV) exploration, which selects the goal configuration anticipated to achieve the largest *information gain* with respect to the robot's occupancy map

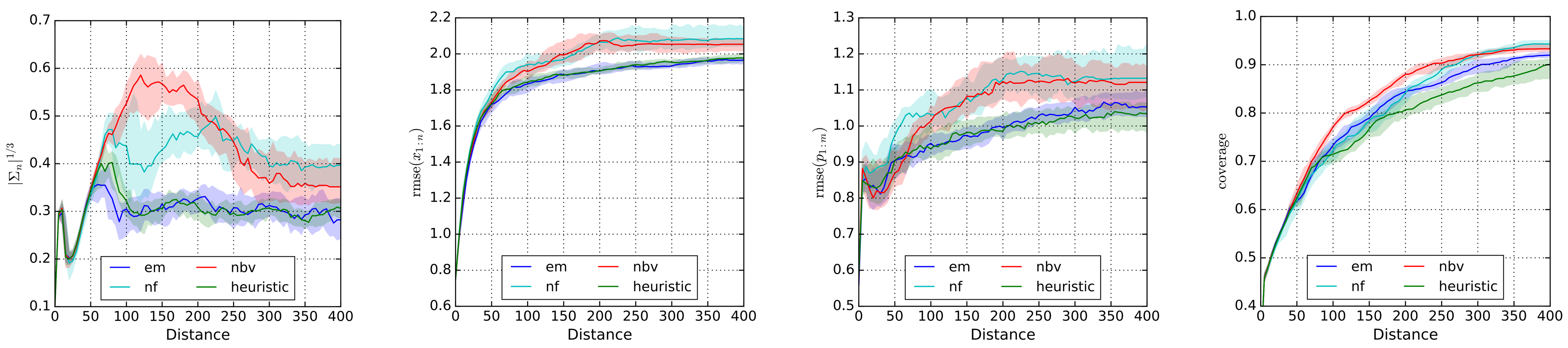


(c) Example of an **active SLAM** framework which selects the place-revisiting goal configuration that maximizes a utility function expressing a weighted tradeoff between uncertainty reduction and information gain, when a robot's *pose uncertainty* exceeds a designated threshold (we term this the Heuristic approach).



(d) Example of our **proposed** E-M algorithm. It balances information gain and uncertainty reduction at every step by planning on a virtual map composed of virtual landmarks acting as proxy for a real feature-based map, on which we are able to predict the uncertainty resulting from future sensing actions.

Figure 3: Pose SLAM simulation examples using NF, NBV, Heuristic and E-M algorithms in a marina environment. Each quadrant shows results from a representative execution trace. In each quadrant at left, the resulting occupancy map with pose history and loop closure constraints is shown. At right, a plot of map coverage, pose uncertainty, map error, and pose error are shown vs. travel distance.



(a) Pose uncertainty **(b)** Trajectory error **(c)** Map error **(d)** Map coverage

Figure 4: Exploration performance mean values in the simulated marina environment for 60 trials starting at different positions, with 95 percent confidence intervals shown. Values along the x-axis denote the robot's distance traveled in meters. NF and NBV algorithms achieve efficient exploration, but at the expense of high error. While the heuristic and EM algorithms have similar pose uncertainty and map/trajectory error, the heuristic approach falls behind EM in terms of map coverage.

REAL EXPLORATION EXPERIMENTS

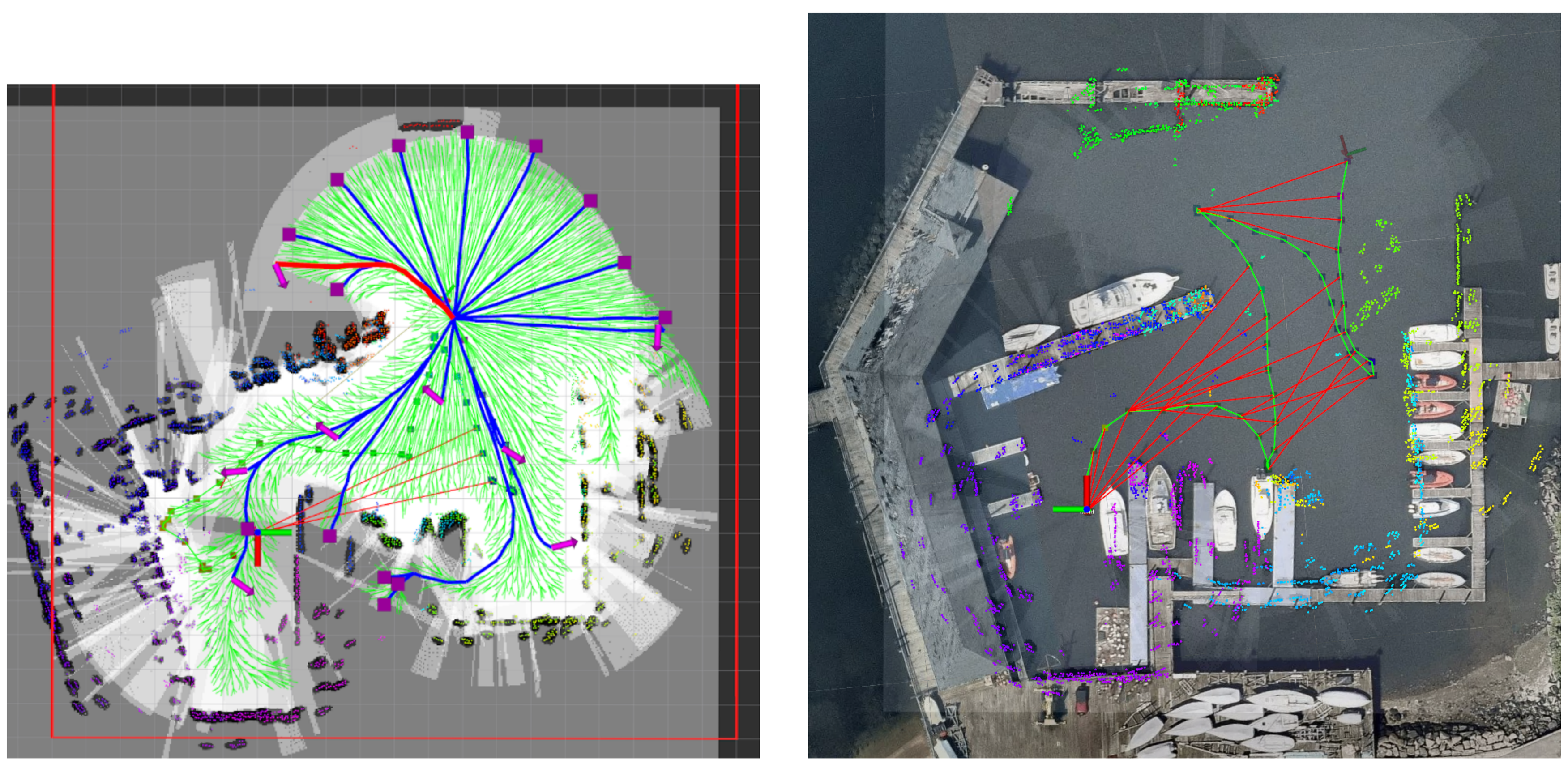


Figure 5: Exploration experiments performed at the U.S. Merchant Marine Academy in King's Point, NY (workspace is about 100m x 100m). **Left**: An example of the motion planning process used to support exploration. Purple squares are frontier candidates, purple arrows are place revisiting candidates. Blue lines are candidate trajectories and the green graph is used for global planning in conjunction with A*. The red trajectory is selected due to an anticipated loop closure and good information gain in the meantime. **Right**: A representative final mapping result from E-M exploration. Our robot's estimated trajectory and loop closures are visualized by the green and red lines, respectively.