Unmanned Systems Research with Maritime Security Applications

Brendan Englot
Assistant Professor of Mechanical Engineering
Stevens Institute of Technology

June 11, 2015
Outline of the Talk

• Brief overview of my prior research activities
• Autonomous Ship Hull Inspection – Path Planning for Sensor Coverage (2009-2012)
• Planning Under Uncertainty (2012-Present)
• Exploration and Mapping with Sparse and Noisy Data (2014-Present)
Overview of Prior Research Activities

- Massachusetts Institute of Technology (Cambridge, MA) 2007-2012
  - Research Assistant, Department of Mechanical Engineering
  - Path Planning in Support of Autonomous, In-Water Ship Hull Inspection (testing and validation on Navy and Coast Guard vessels)
Overview of Prior Research Activities

- United Technologies Research Center (East Hartford, CT) 2012-2014
  - Sikorsky Aircraft Corporation: Contributor to Development of the Sikorsky Autonomous Research Aircraft (SARA)

- Applications of Interest: Safe flight in obstacle-rich environments, shipboard landing, cargo transport
Overview of Prior Research Activities

- United Technologies Research Center (East Hartford, CT) 2012-2014
  - Autonomous and Intelligent Robotics Laboratory (AIRLab):
    Principal Investigator in Low-Level Autonomy Area

- Robust, Hierarchical Planning of Complex Missions via Multi-Objective Planning and Optimization
Robust Field Autonomy Lab
Department of Mechanical Engineering

- PI: Brendan Englot, 3 Ph.D. Students, 2 M.S. Students, 2 Undergraduate Students
- Goal: Develop control systems and algorithms that extend the reach of autonomy into complex environments
Robust Autonomy for Structure Monitoring

• Developing new and promising methods for autonomous operation in the close vicinity of offshore structures, suitable for varying amounts of prior information:
  • High-precision inspection of a known environment
  • Navigating a known environment under uncertainty
  • Exploring an unknown environment

• Long term goal: comprehensive, continuous, and multi-domain (air, surface, and subsea) structural health monitoring

Devaurs, Simeon and Cortes, WAFR 2014
Outline of the Talk

• Brief overview of my prior research activities

• Autonomous Ship Hull Inspection – Path Planning for Sensor Coverage (2009-2012)

• Planning Under Uncertainty (2012-Present)

• Exploration and Mapping with Sparse and Noisy Data (2014-Present)
Hovering Autonomous Underwater Vehicle (HAUV)

- Free-floating, fully actuated (in 6 D.O.F.), hover-capable robot
- Perform autonomous, in-water ship hull inspection to detect mines
- Joint effort by MIT Sea Grant and Bluefin Robotics, beginning 2002
- Now produced by Bluefin, 15 ordered by US Navy for inspections
A Full-Coverage Hull Inspection: Forward Hull

- “Non-Complex Areas” (~80% of ship)
- HAUV navigates relative to the hull, DIDSON collects 2D images

Back-and-forth sweeping covers the forward sections
Using Sonar as a Navigation Aid

Hover, Eustice, Kim, Englot, Johannsson, Kaess and Leonard
IJRR 2012
Using a Camera as a Navigation Aid

- Small field of view, limited viewing range in turbid water.
- However, when structures are feasible, imagery often contains rich visual feature content that is beneficial for navigation.
- Imagery above the surface can be used to aid the sub-sea navigation process.
Using a Camera as a Navigation Aid

(a) Raw imagery for two keyframes $i$ and $j$.

(b) Radially undistorted and histogram equalized imagery.

(c) Extracted SIFT features.

(d) Pose constrained correspondence search (PCCS).

(e) Putative correspondences resulting from PCCS.

(f) Resulting inliers from geometric model selection framework.
A Full-Coverage Hull Inspection: Stern

- “Complex Areas” (~20% of ship)
- HAUV navigates relative to seafloor, DIDSON collects range scans
- Aviation Logistics Ship SS Curtiss shown as a motivating example:

How should we pursue full coverage at the stern?

- Propeller (7m diameter)
- Shaft (1.5m diameter)

Englot and Hover, IJRR 2013
An Example of the Desired Result

- Stabilize at each of a series of waypoints
- Pitch the sensor through its full range of motion at each waypoint to collect a volumetric scan
- Plan an efficient collision-free path that achieves 100% coverage of the hull among all view configurations
Sampling-Based Path Planning

• Rather than optimize over problem geometry, sample robot configurations and incrementally construct feasible solution

• Project each sample from robot's Configuration Space (C-Space) to the Euclidean Workspace to check against constraints

• Goal is to efficiently connect the free space despite high D.O.F., complex geometry, and challenging constraints/costs

Probabilistic Roadmap (PRM) (Kavraki et al. 1996)
A Sampling-Based Planning Approach

- Coverage problem is solved by Monte Carlo sampling, a probabilistic roadmap (PRM) is used as the basis for constructing an inspection route.
- Sampling is limited to regions where the structure is within viewing range, occurs until requisite sensor coverage of the structure is achieved.
- Coverage-based sampling approach shown to be probabilistically complete with exponential convergence to a feasible solution.

Englot and Hover, IJRR 2013
Producing a Locally Optimal Inspection Route

- Randomized inspection tours are substantially improved by iterative sampling procedure to replace existing configurations
- Coverage is maintained while locally shortening the length of the inspection tour
Heat maps show the relative algorithm runtime required to obtain coverage of each primitive in the mesh.

- Majority of both structures is open and accessible.
- Is it possible to improve regularity in the survey of these open areas?
- Regularized planning approach segments the structure and covers as much as possible using uniform, sweeping patterns.

Englot and Hover, IROS 2012
Results from Field Experiments

- USCGC Seneca, Boston Harbor, 2012 – Planned and Deployed a Full-Coverage Stern Inspection
- Planned vs. Obtained views used to improve initial, coarse model
Lessons Learned: Planning Adaptively, and Under Uncertainty

- **Adaptive Planning:** Revise the mission in real-time based on the data acquired; we will always see more or less of the structure than intended.

- **Robust Planning:** Propagate uncertainty (process and sensor noise) over planned paths, plan a series of measurements that offers guarantees on collision probability and structure coverage.
Outline of the Talk

- Brief overview of my prior research activities
- Planning Under Uncertainty (2012-Present)
- Exploration and Mapping with Sparse and Noisy Data (2014-Present)
Toward Robust Path Planning

• Robust path planning requires:
  • Reliable models of vehicle dynamics and the surrounding environment
  • A collision-free plan
  • Confidence that vehicle will follow the trajectory as planned

• To obtain the latter, we must simulate the execution of the plan
  • Goal is to complete the plan with high likelihood of successful arrival

• Must propagate uncertainties over candidate paths under anticipated actions and measurements

Patil, van den Berg and Alterovitz, ICRA 2012
Prior Work in Planning Under Uncertainty

- Algorithms have been proposed for planning under uncertainty in:
  - Actions [Alterovitz et al. 2007]
  - Environment Map [Missiuro and Roy 2006, Guibas et al. 2008]
- Assuming Gaussian noise in actions and measurements, candidate plans may be evaluated by propagating a Kalman Filter over candidate paths – The Belief Roadmap Algorithm (BRM)
- BRM minimizes uncertainty in vehicle state, at the goal state – trace of error covariance matrix is the scalar metric of uncertainty

The Belief Roadmap (BRM)
Prentice and Roy, IJRR 2009
Environment Likely to Induce Sensor Failures

- Not only will sensors return measurements with additive noise, sometimes they will fail to produce a measurement altogether.
- Probability of a “misdetection” may depend on:
  - Obstacle locations
  - Lighting conditions
  - Material composition
- If we understand the source of this probability, we can include this in the planning process.
- Applicable to range beacons, environment features measured by camera or laser.

Bopardikar, Englot and Speranzon ICRA 2014
Path Planning with a Novel Uncertainty Metric

- A novel uncertainty metric (which upper bounds the error covariance maximum eigenvalue) is used to identify the path of minimum goal-state uncertainty under probabilistic measurements, actions, and misdetections.

- A probabilistic roadmap (PRM) is used as the basis for selecting paths, and the search is adapted from the belief roadmap (BRM) algorithm – a best-first search similar to Dijkstra’s algorithm, with non-additive costs.

- UWB range beacons (10% successful) and obstacle corners (90% successful) are characterized by different misdetection probabilities.
Planned Paths Depend on Reliability of Sensors

- Laser has a higher sensor noise covariance than beacons do at close range – beacons are preferred for reducing uncertainty until a reliability threshold is reached.

- Beyond this threshold, robot takes a lengthy detour to collect laser measurements of the obstacles; not as precise as beacon measurements but they are more reliable.
Implementation of a Larger-Scale Test Case

- Reliability of laser-based feature detection depends on lighting conditions.
- Algorithm plans over a square-kilometer block of an urban environment using dense PRM.
- Neglecting environment-induced intermittency, probability of collision with surrounding obstacles is dangerously high.
Variable-Resolution Planning Under Uncertainty

- Use an expanded graph that represents varying levels of uncertainty in the localization process.
- Search the graph to achieve a minimum-cost path subject to desired upper limit on uncertainty.
- Typical issues with history dependence in planning under uncertainty are addressed by graph organization scheme (all nodes have the same cost associated with belief).

Bopardikar, Englot and Speranzon ACC 2014
• Use an expanded graph that represents varying levels of uncertainty in the localization process

• Search the graph to achieve a minimum-cost path subject to desired upper limit on uncertainty

• Typical issues with history dependence in planning under uncertainty are addressed by graph organization scheme (all nodes have the same cost associated with belief)
Improving on Optimal Search

• Given a probabilistic roadmap or other representative graph, our approaches thus far emphasize search methods – why not construct a graph with optimal limiting behavior?

• This perspective typically emphasizes tree-based graphs used only once by the robot, planning from its current location to others

• The search of a tree is trivial, but construction to achieve asymptotically optimal limiting behavior is not

• A key challenge in optimal tree construction is optimization with respect to a fluctuating cost – robot uncertainty – rather than an additive cost, such as distance, time, or fuel consumption

• We will attempt to capture the spirit of minimizing the “mean” uncertainty while obeying the required optimality criteria
• Proposal: plan a path of **minimum max uncertainty** as captured using the robot’s state estimate error covariance

• We assume our robot navigates using odometry and GPS to localize, but GPS availability is limited to specific zones (depicted in yellow)

• Minimizing cumulative uncertainty will bias the solution in favor of short paths – these may contain individual states of high uncertainty
Comparison of Three Cost Criteria

After 5,000 Samples:

• Comparison of min-max approach with standard min-distance approach (left) and a cumulate uncertainty approach (center)

• Cumulative vs Min-Max approaches generate some solutions of different homotopy
Comparison of Three Cost Criteria

After 10,000 Samples:

- Comparison of min-max approach with standard min-distance approach (left) and a cumulate uncertainty approach (center)
- Cumulative vs Min-Max approaches generate some solutions of different homotopy
Comparison of Three Cost Criteria

After 20,000 Samples:

- Comparison of min-max approach with standard min-distance approach (left) and a cumulate uncertainty approach (center)
- Cumulative vs Min-Max approaches generate some solutions of different homotopy
Outline of the Talk

• Brief overview of my prior research activities
• Autonomous Ship Hull Inspection – Path Planning for Sensor Coverage (2009-2012)
• Planning Under Uncertainty (2012-Present)
• Exploration and Mapping with Sparse and Noisy Data (2014-Present)
Planning Over Uncertain and Data-Derived Maps

- Robot mapping is largely focused on ground and aerial platforms with high-precision, well-behaved sensors (Kinect, Hokuyo)
- Occupancy grid mapping is a highly successful approach amenable to planning and exploration over a data-derived map
- Typically no consideration of the underlying probability distribution in the planning process
- Thresholding is often applied to the map; all cells assumed independent; no consideration of underlying sensing process
Planning Over Uncertain and Data-Derived Maps

- For underwater, sonar-based occupancy grid mapping and navigation to succeed, must utilize sparser, noisier data
- Gaussian process regression succeeds at capturing correlation and properties of underlying sensor – a sound basis for planning
- Goal: Develop algorithms for efficient and safe planning over the rich probability distributions associated with GP occupancy grid maps – a complement to min. localization uncertainty planning
Tools for Efficient Exploration of Unknown Environments

- 3D Frontiers Derived from GP Occupancy Maps, an aid for deciding where to explore next (top, left)
- GP regression over continuous, spatial action spaces, predicting the most informative sensing action (top, center)
- Multi-Resolution Gaussian Process occupancy maps (bottom, left)
Experimental Goals

• Develop algorithms using sound theory and analysis that achieve high performance in real-time, over real data

• Clearpath Turtlebot is our rapid prototyping platform for validation of algorithms over sensor data and real-time, feature-based autonomous navigation processes

• Final testing and validation of algorithms through rigorous experimentation on a marine robot platform, VideoRay Pro 4 remotely operated vehicle (ROV)
On the Hudson River this Spring
Thanks for listening!

Complex, highly cluttered seabed in a confined area

Questions?