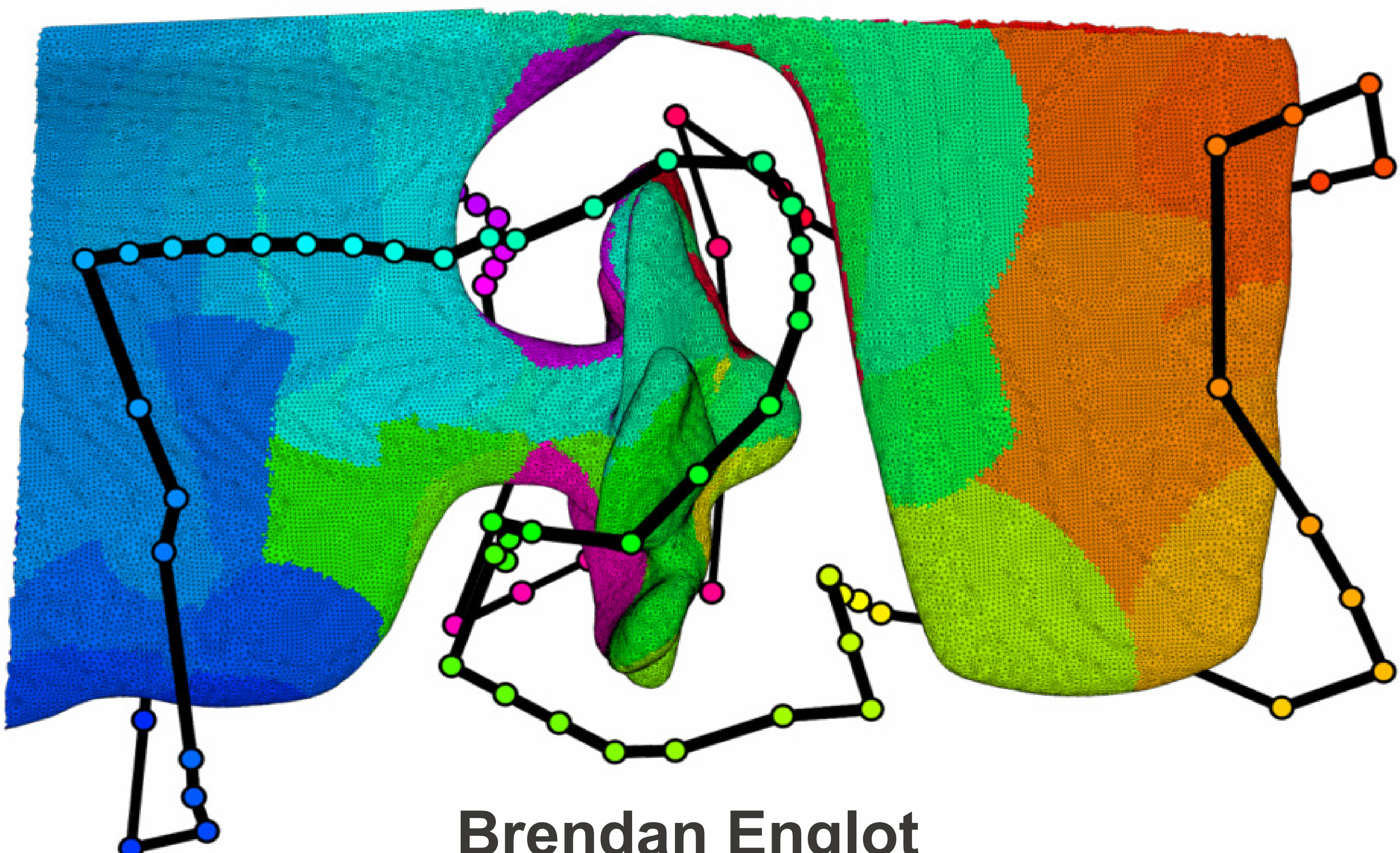
Sampling-Based Coverage Path Planning for Inspection of Complex Structures



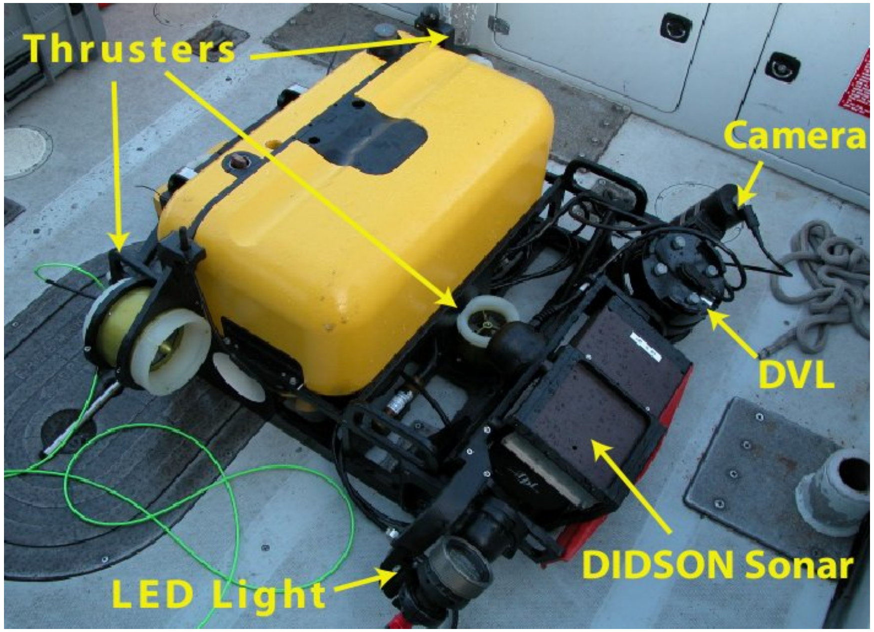
Brendan Englot
Prof. Franz Hover

Department of Mechanical Engineering
Massachusetts Institute of Technology

Outline of Presentation

- Introduction: Motivation, Problem Statement, Relevant Background
  - Autonomous, In-Water Ship Hull Inspection
  - Why is Sampling-Based Coverage Planning Needed?
- Analysis of Sampling-Based, Feasible Coverage Path Planning
  - Solved in two phases, view planning and multi-goal planning
  - Detailed look at probabilistic completeness of sampling-based view planning
- Improvement Algorithm for Shortening Feasible Routes
  - Theoretical Guarantees and Computational Results
- Experimental Implementation of Algorithms
  - Execution of Planned Inspection on US Coast Guard Cutter

Hovering Autonomous Underwater Vehicle (HAUV)

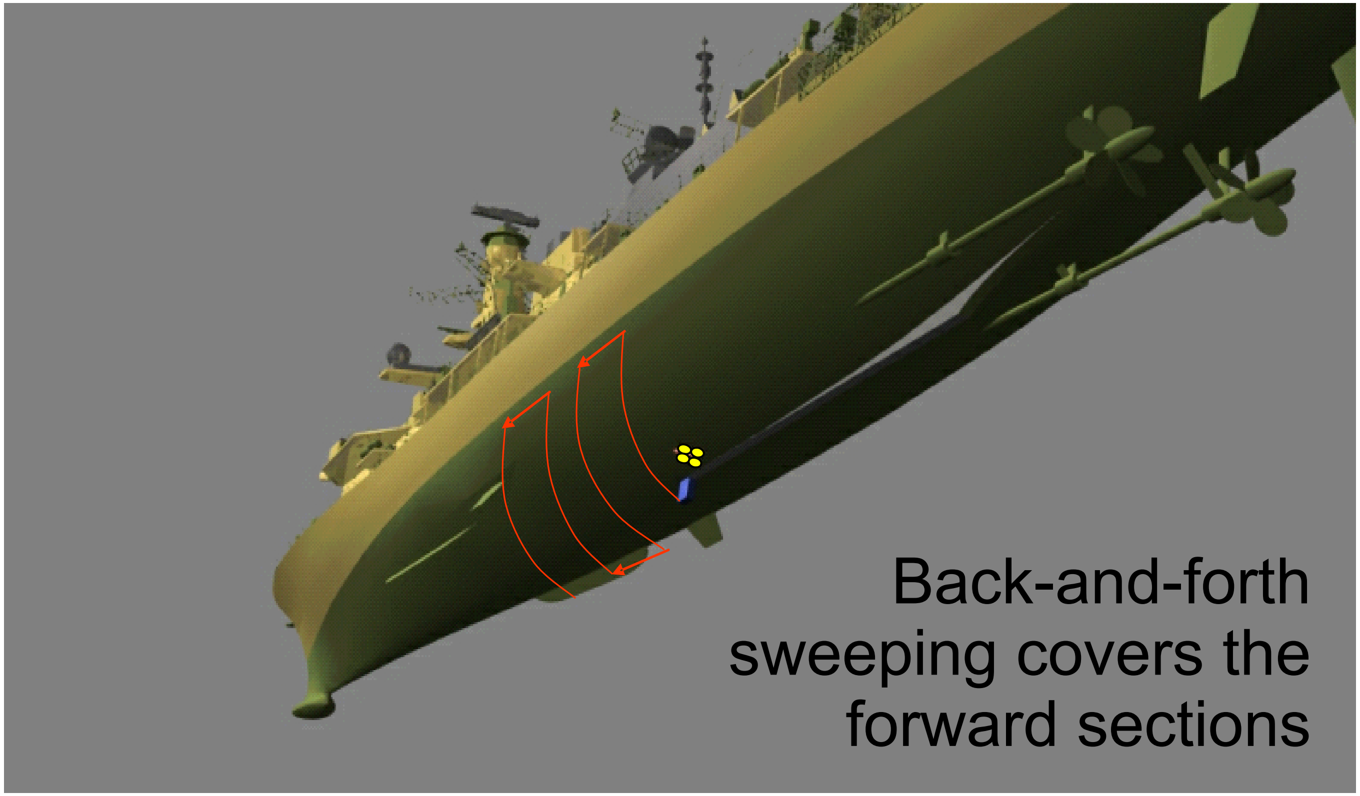


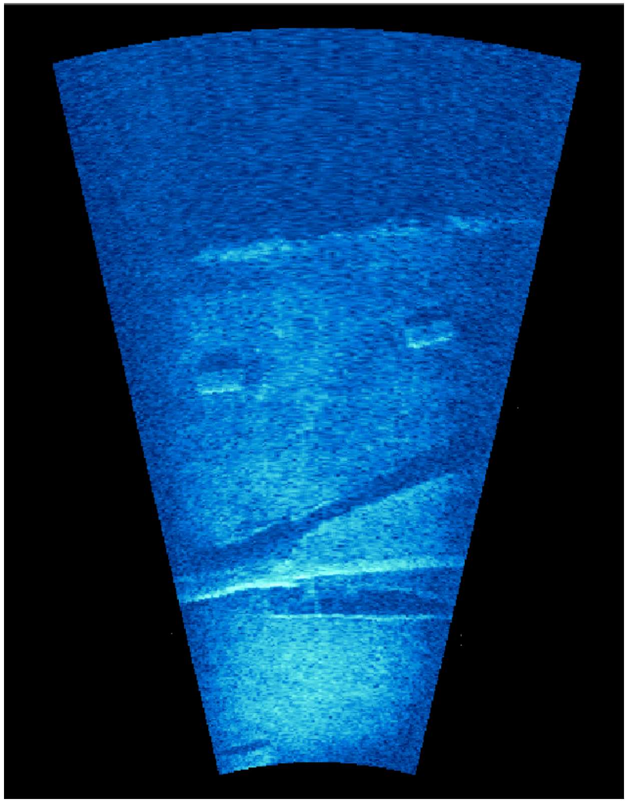
- Free-floating, fully actuated (in 6 D.O.F.), hover-capable robot
- Goal: Autonomous in-water ship hull inspection to detect mines
- Joint effort by MIT Sea Grant and Bluefin Robotics, beginning 2002
- Now produced by Bluefin, 15 ordered by US Navy for inspections

A Full-Coverage Hull Inspection: Forward Hull

"Non-Complex Areas" (~80% of ship)

HAUV navigates relative to the hull, DIDSON collects 2D images





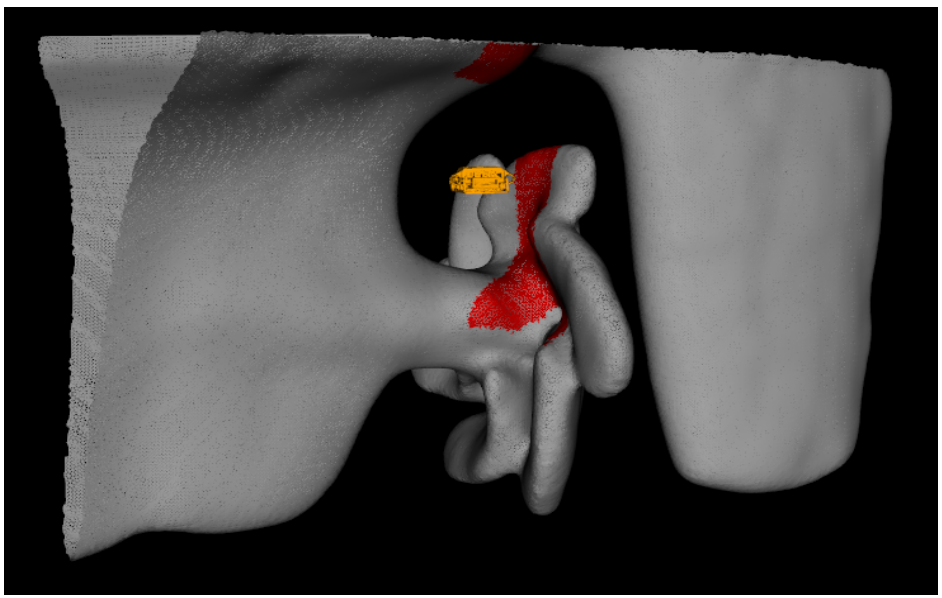
Ongoing efforts to achieve accurate localization over long time scales

A Full-Coverage Hull Inspection: Stern

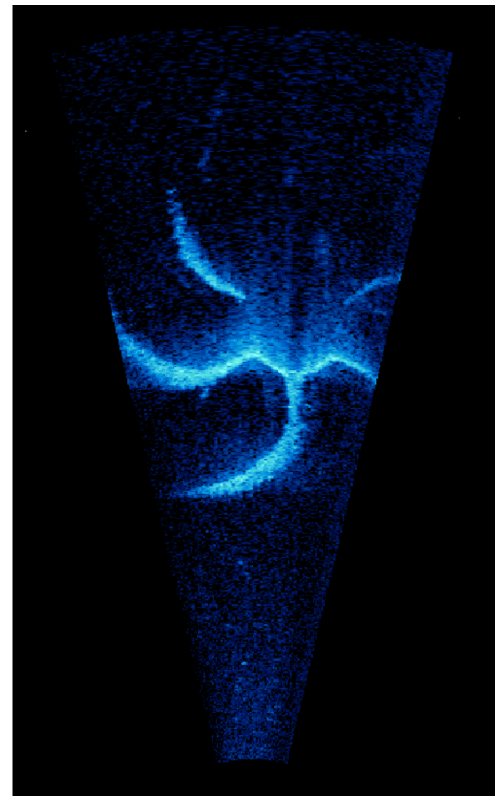
"Complex Areas" (~20% of ship)

HAUV navigates relative to the seafloor, DIDSON collects range scans

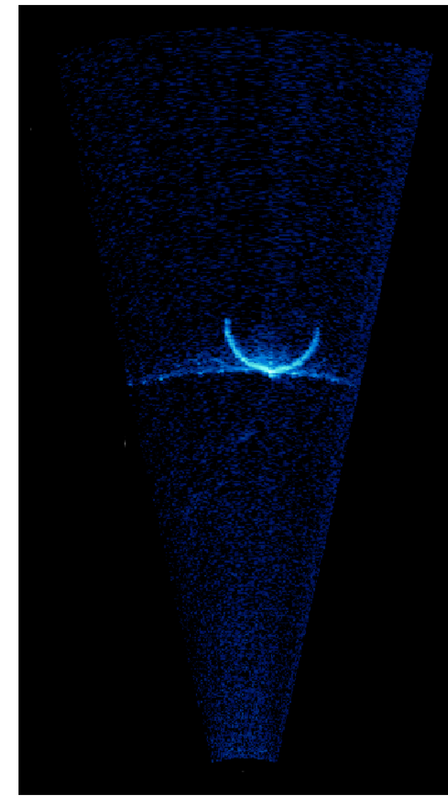
Aviation Logistics Vessel *SS Curtiss* shown as a motivating example:



How should we pursue full coverage at the stern?



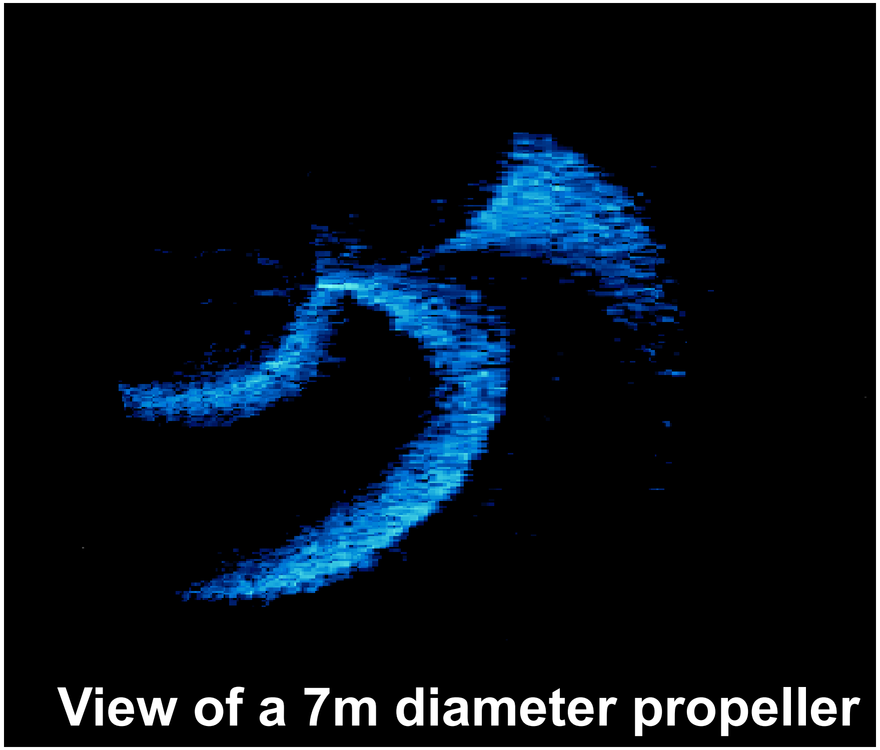
Propeller (7m diameter)

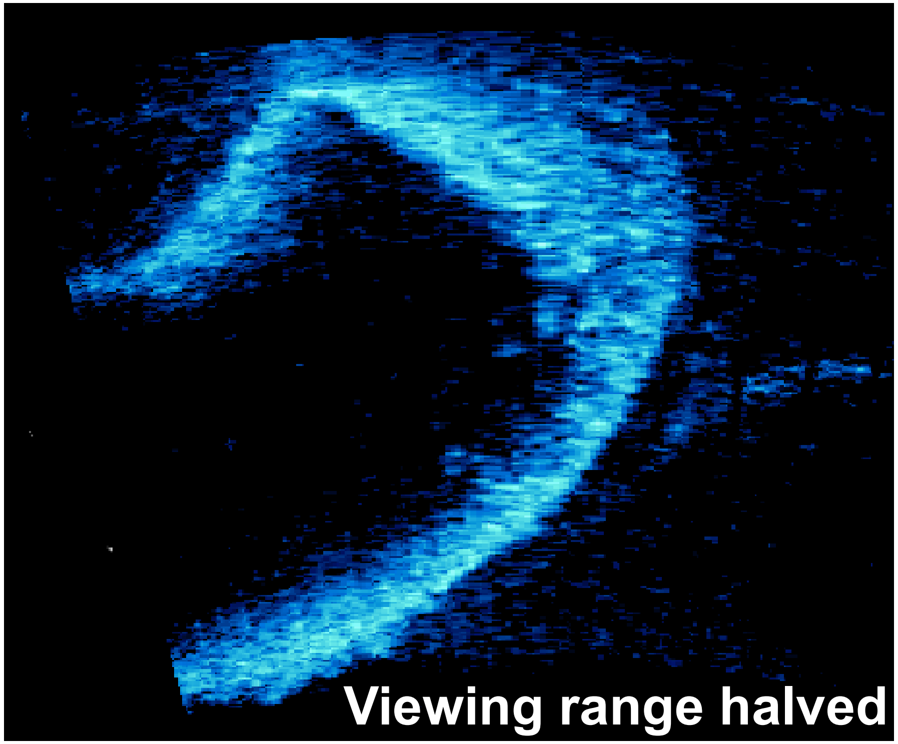


Shaft (1.5m diameter)

A Full-Coverage Hull Inspection: Stern

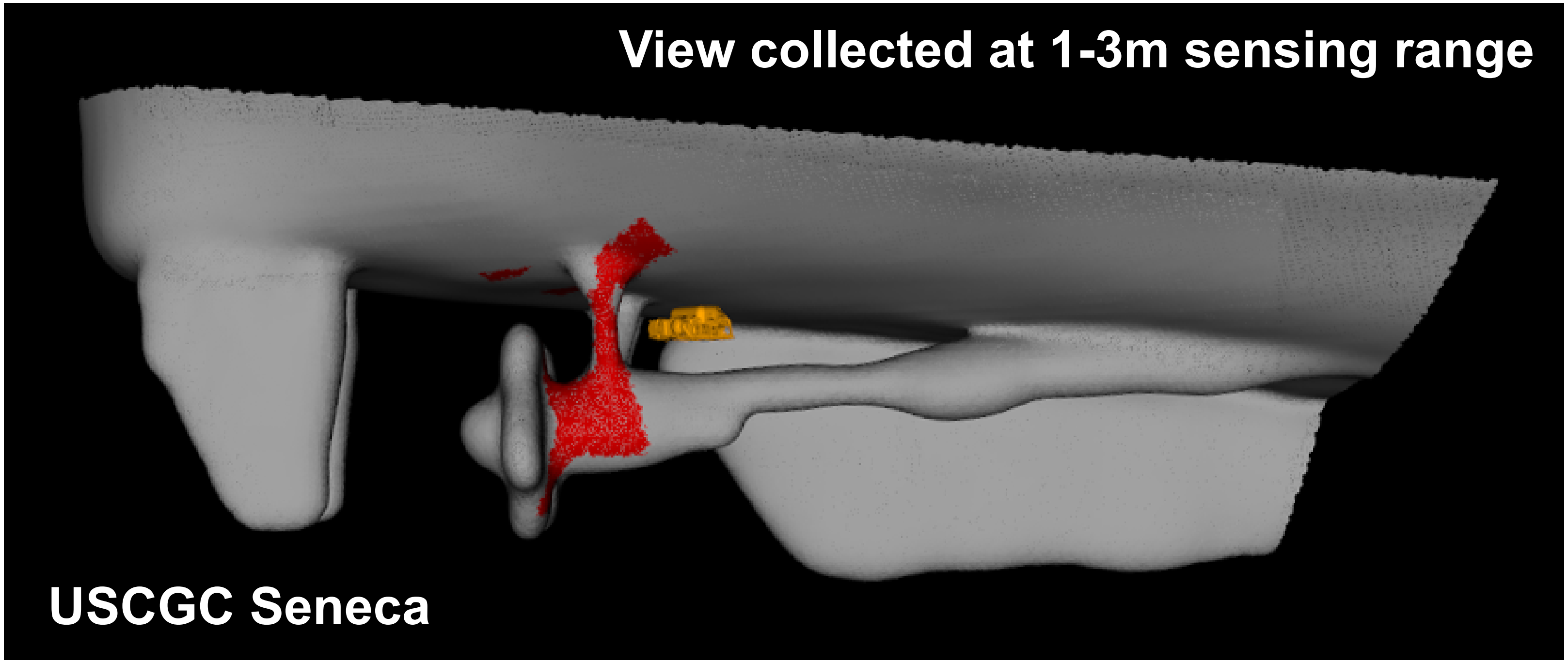
Improved Resolution at Reduced Range





- Sensor tradeoff: shorter range, higher-resolution scans
- Desirable to inspect stern at short range to support mine detection
- Must cover an expansive structure with a small field-of-view sensor

Assumptions on Robot



- While stationary, HAUV pitches sensor 180°, collects volumetric sample
- Four degrees of freedom: HAUV currently not capable of aggressive roll/pitch maneuvers, will plan in x, y, z, and yaw
- Every scan has 30° aperture, we will typically assume 1-3m range

Problem Statement

- **Input:** mesh model of structure, mesh model of robot, geometry of the sensor field of view
- **Output:** a collision-free inspection tour that observes every vertex in the structure model (other primitives can be specified)
- **Key Assumptions:** a model-based, geometric path planning problem with sensing at discrete locations
  - **Model-Based:** use CAD or data-derived model, must cover an expansive structure with a limited field-of-view, slow moving robot
  - **Geometric:** HAUV dominated by drag, feasible positioning & observation of occluded areas are the key challenges
  - **Discrete:** robot stabilizes and sweeps sensor at each individual waypoint, easier to implement in the presence of disturbances

An Example of Desired Output

Contributions

- The first probabilistic completeness analysis applied to robot coverage path planning
  - Analysis tools from collision-free path planning augmented to accommodate coverage constraints
  - We bound the convergence of sampling-based routines using decaying exponential functions
- An improvement algorithm that iteratively shortens coverage routes
  - Compatible with RRT* path planning algorithm; retains its optimality properties in the solution of a local sub-problem
  - Computational proof-of-concept: significant improvements made to feasible coverage routes
  - A planned inspection route has been executed at the stern of a US Coast Guard Cutter

Prior Work in Coverage Planning: 2D Structures

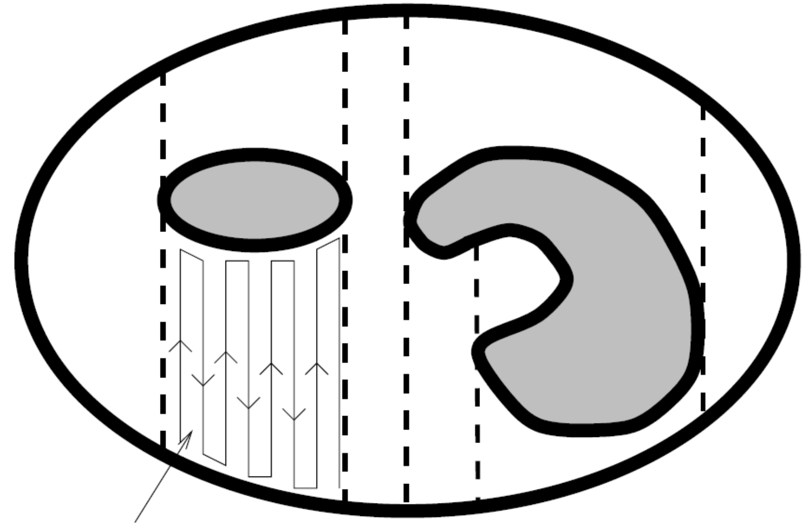
Path Planning for Continuous Coverage

Cell Decomposition

(Zelinsky et al. 1993)
(Choset & Pignon 1997)
(Choset 2001 – Survey)
(Gabriely & Rimon 2001)
(Huang *et al.* 2001)
(Acar *et al.* 2002)
(Mannadiar & Rekleitis 2010)

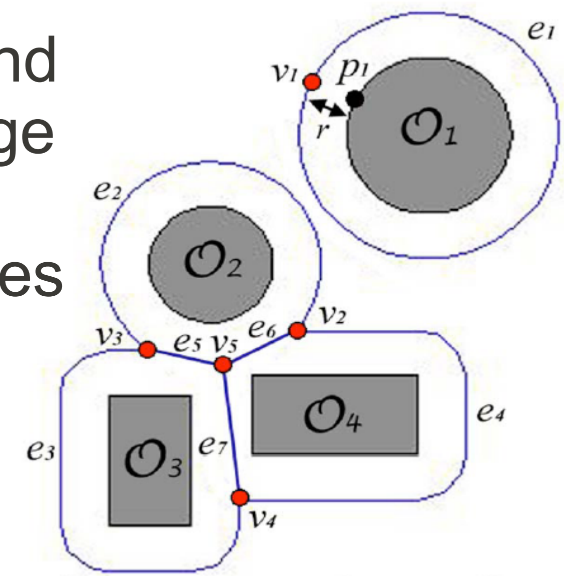
Generalized Voronoi Graphs

(Acar *et al.* 2006)
(Easton & Burdick 2005)



Coverage Path in a Cell

Floor coverage and boundary coverage addressed using different techniques

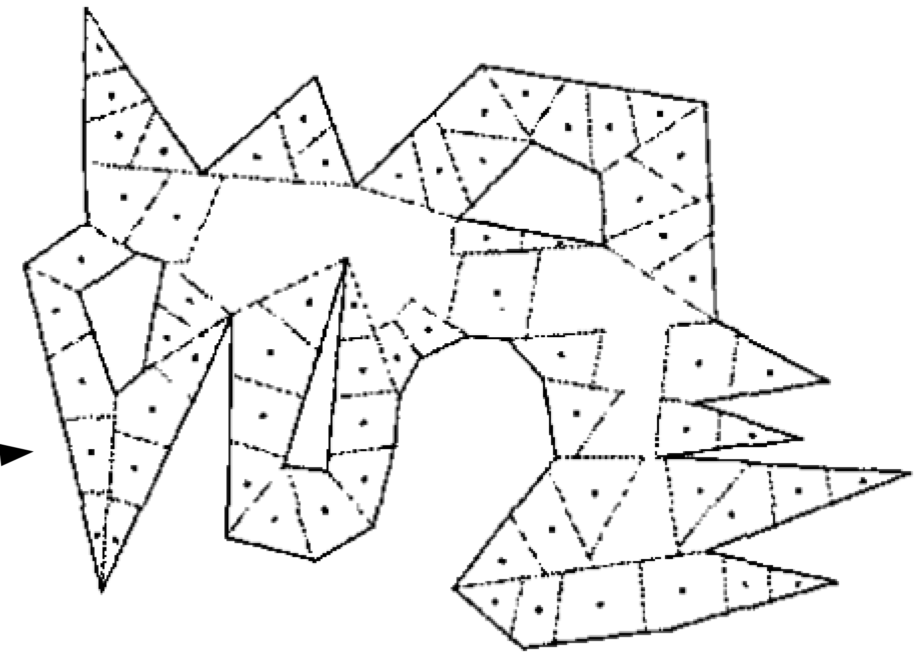


Prior Work in Coverage Planning: 2D Structures

View Planning for Discrete Coverage

"Art Gallery" Combinatorial Algs.

(Shermer 1992 - Survey)
(Kazazakis & Argyros 2002)



Integer Programming

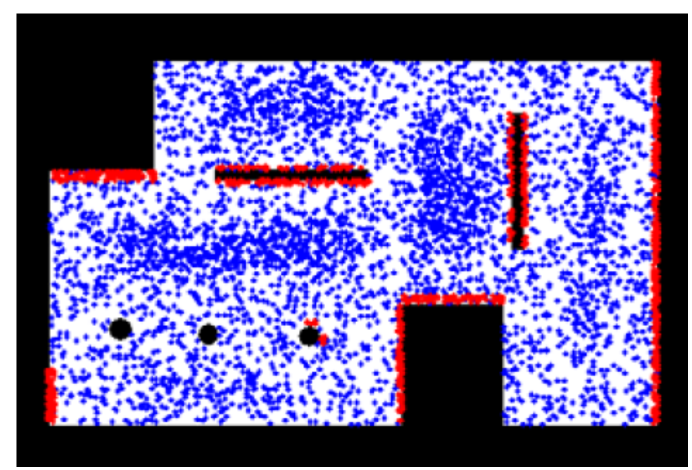
(Erdem & Sclaroff 2006)

Genetic Algorithms

(Yao et al. 2002)

Random Sampling

(Gonzalez-Baños & Latombe 2001)
(Hörster & Lienhart 2006)



Prior Work in Coverage Planning: 3D Structures

Continuous Coverage

Cross-Sectional Loop Paths

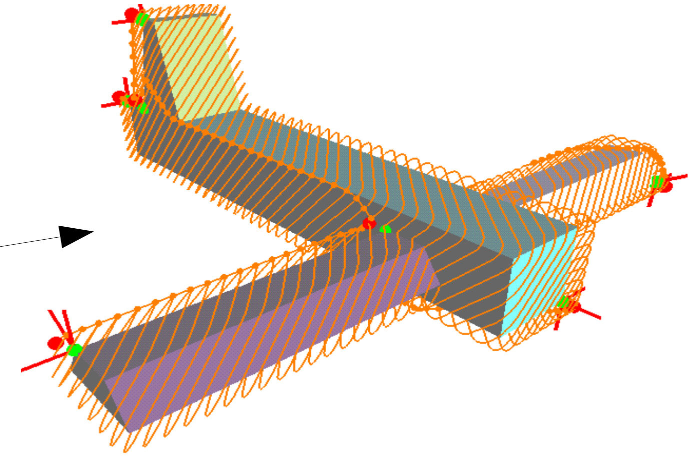
(Atkar *et al.* 2001)
(Cheng *et al.* 2008)

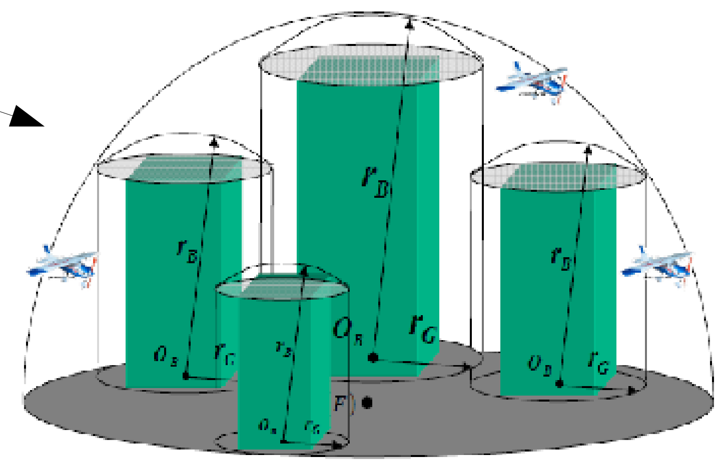
Generalized Vornonoi Graphs

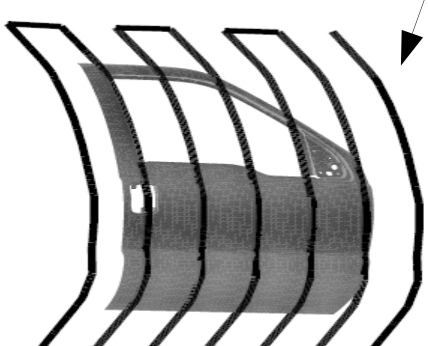
(Choset *et al.* 1999)

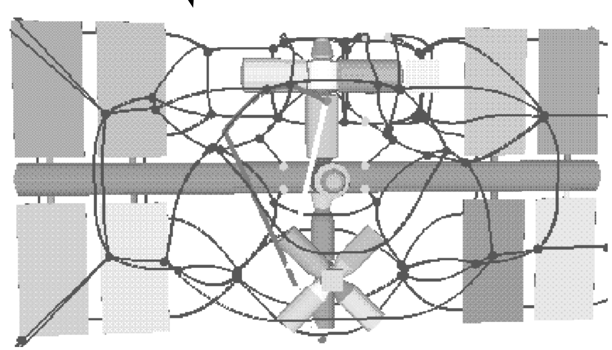
Segmentation of Large Structures

(Atkar *et al.* 2005)

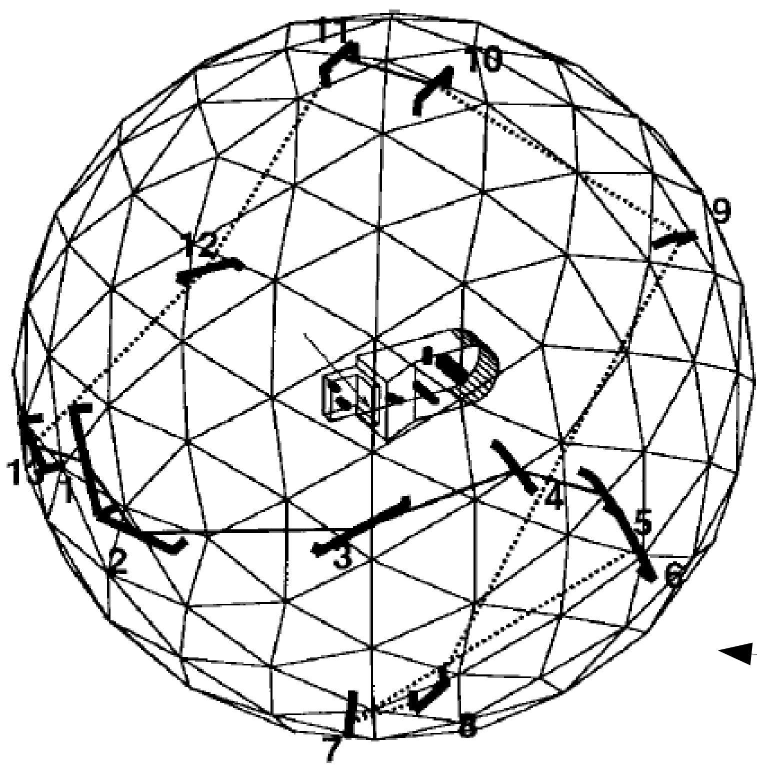








Prior Work in Coverage Planning: 3D Structures



Discrete Coverage

2D View Planning for 3D Structures

(Gonzalez-Baños & Latombe 1998)
(Blaer & Allen 2009)

"Turntable" Coverage of Small Objects

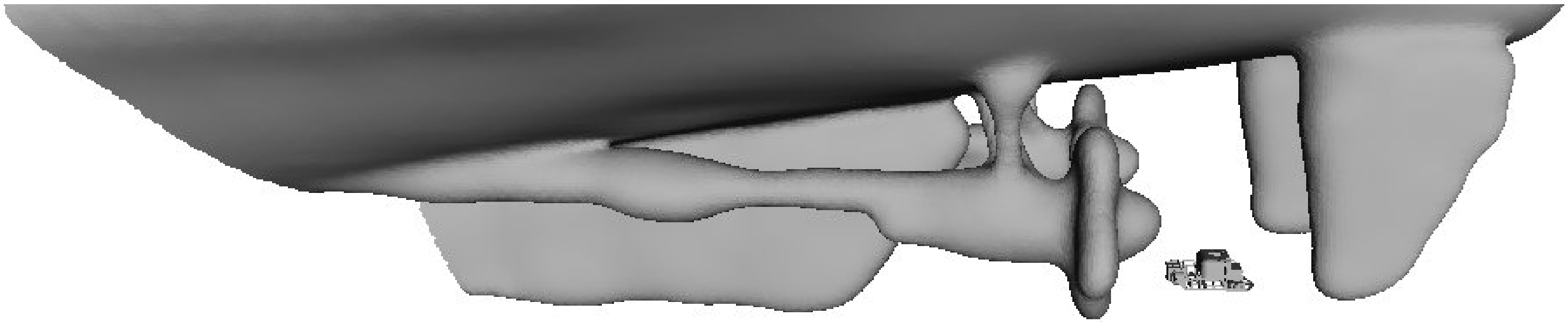
(Tarabanis 1995 – Survey)
(Trucco *et al.* 1997)
(Chen & Li 2004)
(Scott 2009)

Sampling-Based, Global 3D Coverage

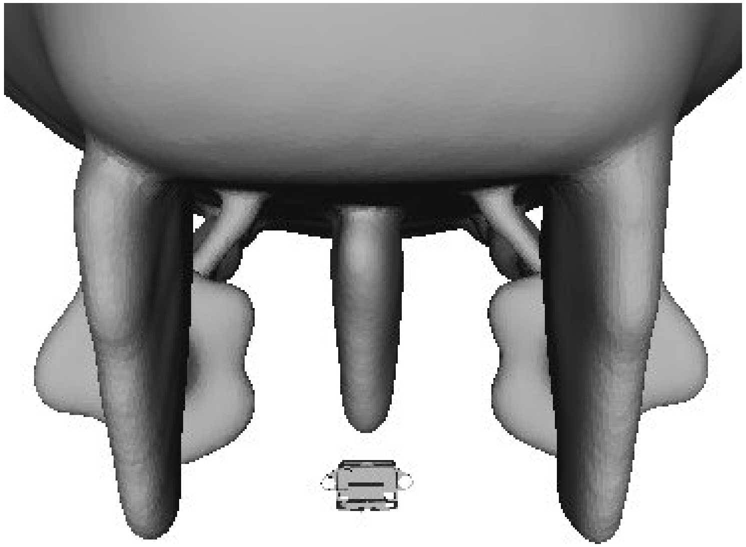
(Danner and Kavraki 2000)
(Englot and Hover 2011)

Suitable for inspecting a **complex, expansive 3D structure** by a **mobile robot** in a disturbance-filled environment

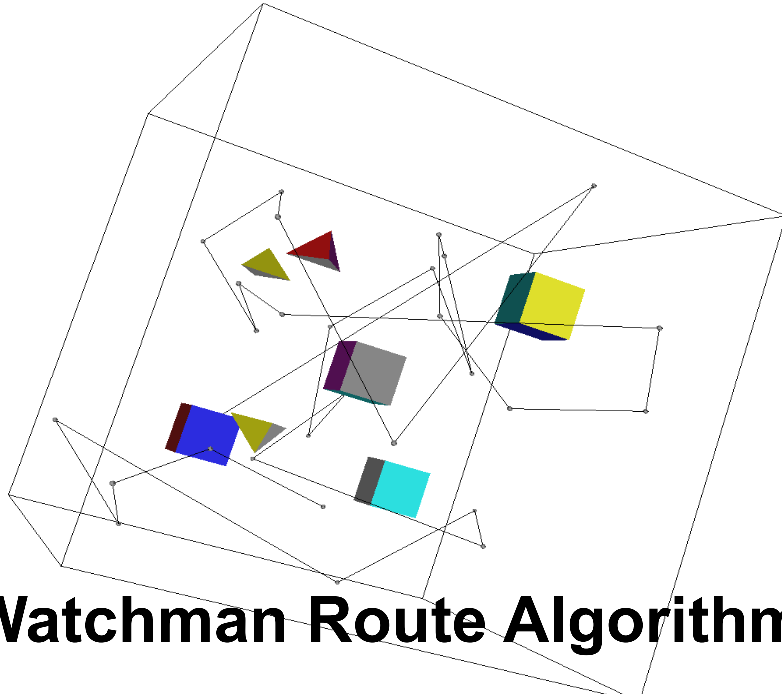
Why Are Other Algorithms Unsuitable?



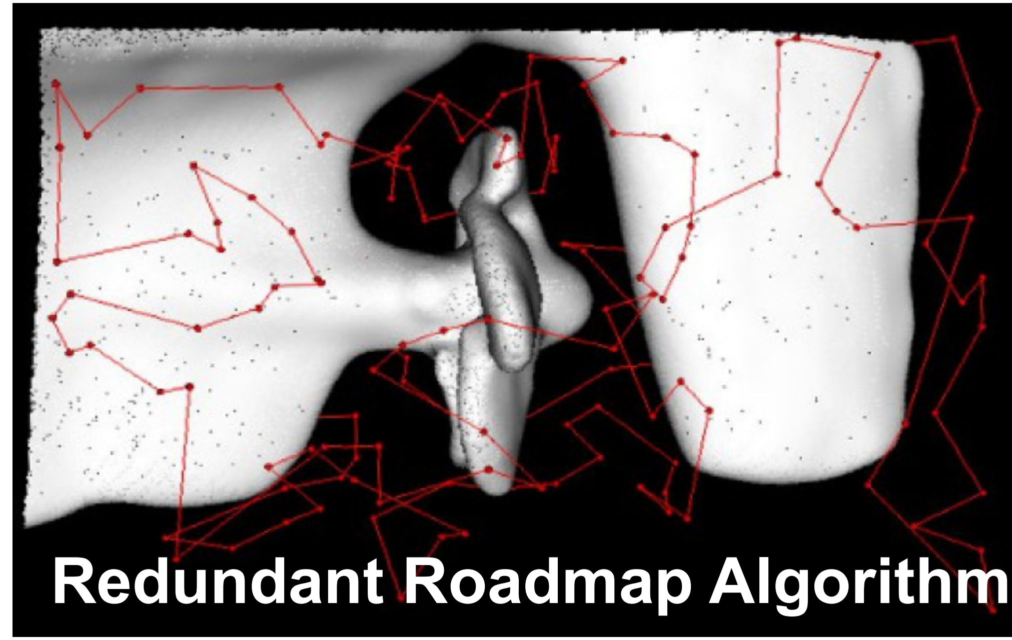
- **Low Clearance** – feasible solutions may not be found if we enforce a single "slicing" direction or reliance on sweep-based primitives
- **Expansive Structure, High D.O.F.** – hard to catalog full coverage topology & solve to optimality over thousands of polygonal faces
- For sampling-based algorithms, we can often establish strong guarantees of **completeness,** meaning feasible solution will be found by algorithm eventually, if one exists



A Two-Stage Sampling-Based Approach



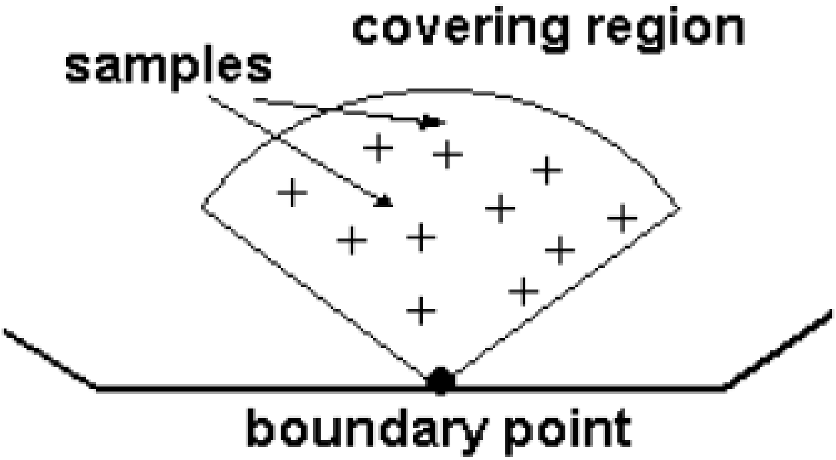
(Danner and Kavraki, 2000)



(Englot and Hover, 2011)

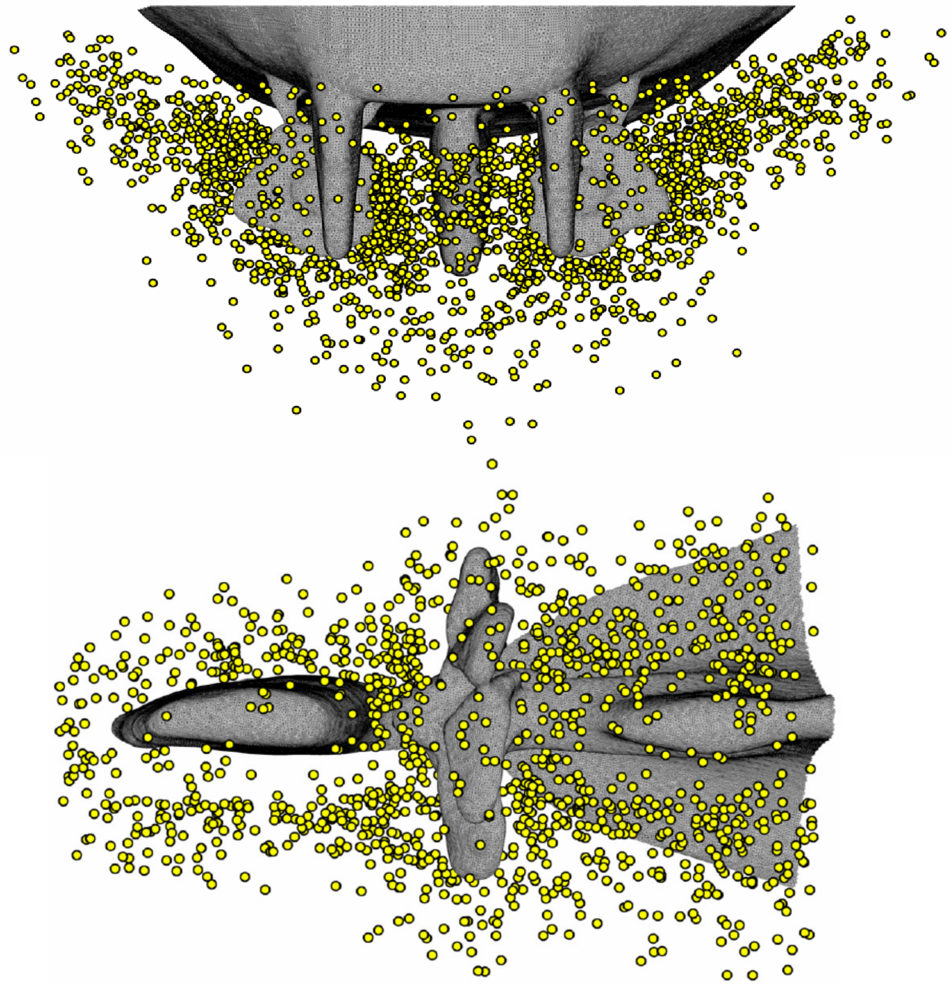
- Stage 1 (**Coverage Sampling**): Sample at random a full-coverage set of sensor views, approximate min-cardinality set cover
- Stage 2 (**Multigoal Planning**): Connect views into a contiguous route using a traveling salesman problem (TSP) approximation to select the ordering, and using view-to-view path planning to find feasible paths

Sampling the Structure Boundary



Dual Sampling

(Gonzalez-Baños & Latombe 1998, 2001)

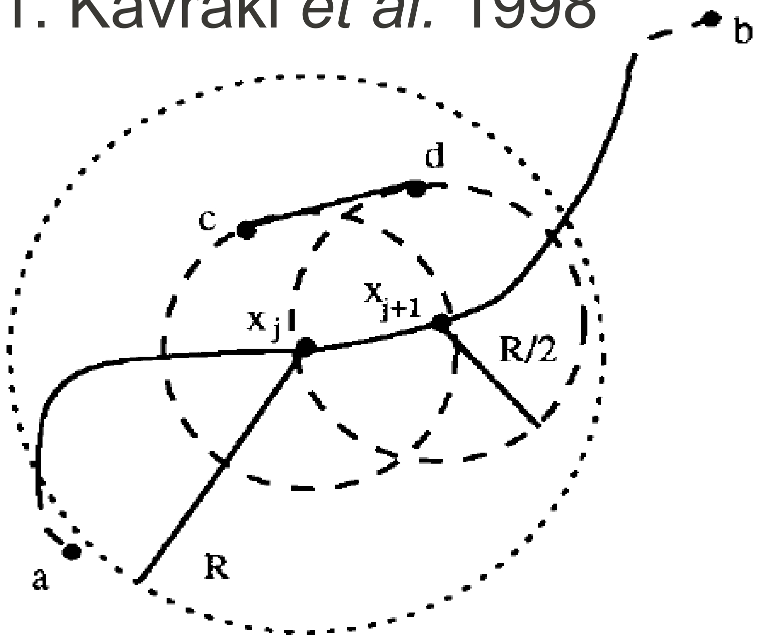


- Choose a location on the structure boundary, sample from local C-Space region that maps to views of the boundary location

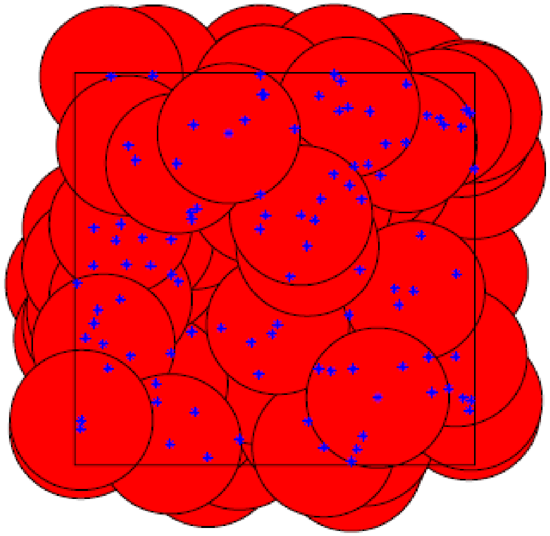
Illustrating the Two-Stage Approach

Algorithm Analysis Concepts

1. Kavraki *et al.* 1998

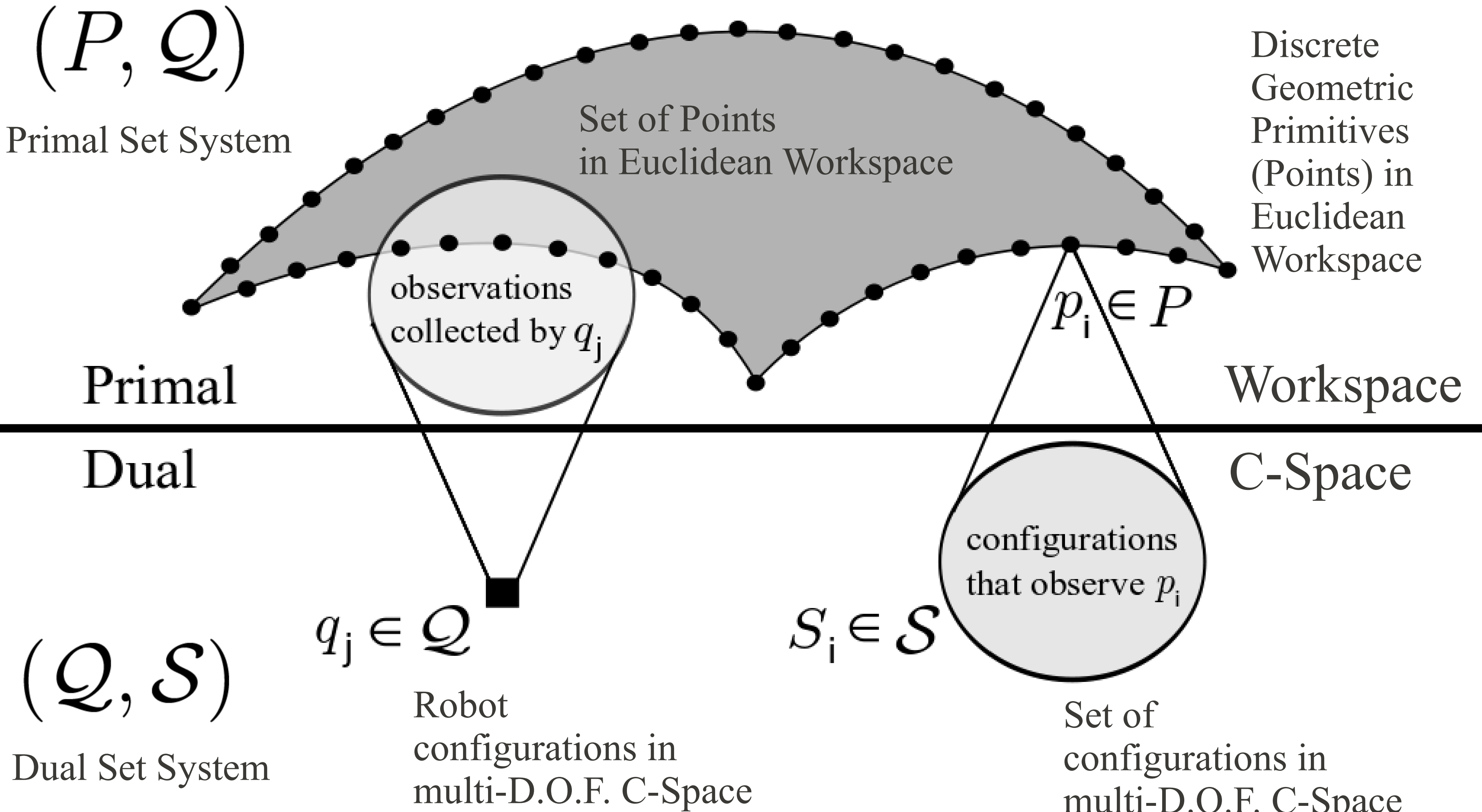


2. Isler *et al.* 2004



- **Path planning algorithms:** analysis of random samples landing in the worst-case regions needed to join *a* and *b* into a feasible path
- **Sensor network algorithms:** number of samples needed for continuous coverage of a structure with high probability
- We adapt these tools to show **coverage of discrete primitives**, less geometry-dependent, more widely applicable

Robot C-Space/Workspace as a Set System



A Definition and Theorem for Coverage Sampling

Def. Probabilistic Completeness. For a dual set system $(\mathcal{Q}, \mathcal{S})$, let $\delta = \min_{S_i \in \mathcal{S}} \mu(S_i)/\mu(\mathcal{Q})$ represent the volume fraction of the smallest set $S_i \in \mathcal{S}$. If, when $\delta > 0$, the probability that **at least *k* samples** have landed in every $S_i \in \mathcal{S}$ approaches one as the number of samples of $\mathcal{Q}$ approaches infinity, then the proposed coverage sampling algorithm is probabilistically complete.

Thm. Probabilistic Completeness. Any coverage sampling algorithm that samples uniformly at random from an infinite subset $A \subseteq \mathcal{Q}$ such that $\mu(S_i \cap A)/\mu(A) \geq \epsilon > 0 \ \forall S_i \in \mathcal{S}$ is probabilistically complete. The probability that a feasible solution has not been found after *m* samples is bounded such that:

$$Pr[FAILURE] < |P| \cdot \frac{e^k}{e^{\,m\epsilon/2}}$$

Where $|P|$ is the number geometric primitives $p_i \in P$.

Proof of Theorem

1) $$Pr[FAILURE] \leq Pr\left[\bigcup_{i=1}^{|P|} X_i < k\right]$$

Binomial random variable

$$\leq \sum_{i=1}^{|P|} Pr[X_i < k]$$

Techniques adapted from: (Kavraki et al. 1998), (LaValle and Kuffner 2001)

Probability of $< k$ successes for at least one $S_i \in \mathcal{S}$

$$\leq |P| \cdot Pr[X_{i*} < k]$$

Assume Poisson, use Chernoff bound

2) $$Pr[X_{i*} < \gamma \cdot \lambda] < e^{-\frac{(1-\gamma)^2}{2}\lambda}, \quad \gamma \in [0, 1)$$

3) $$Pr[X_{i*} < k] < \frac{e^k}{e^{m\epsilon/2}}, \ \lambda = m\epsilon, \ \gamma = k/m\epsilon$$

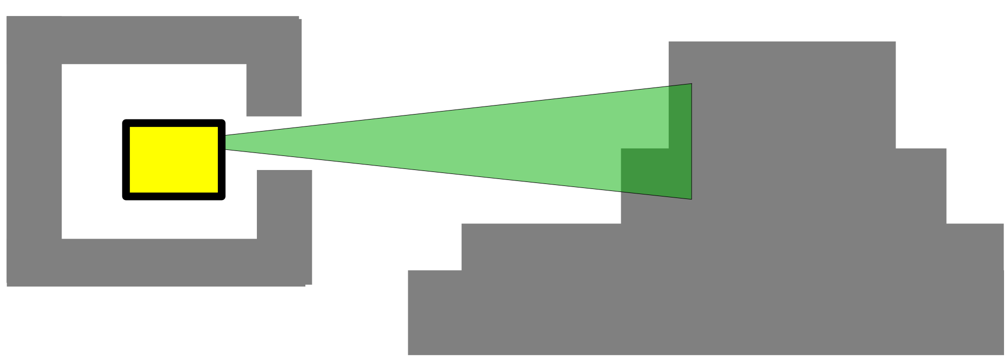
4) $$Pr[FAILURE] < |P| \cdot \frac{e^k}{e^{m\epsilon/2}}, \quad \lim_{m\to\infty} |P| \cdot \frac{e^k}{e^{m\epsilon/2}} = 0$$

Implications of Theorem

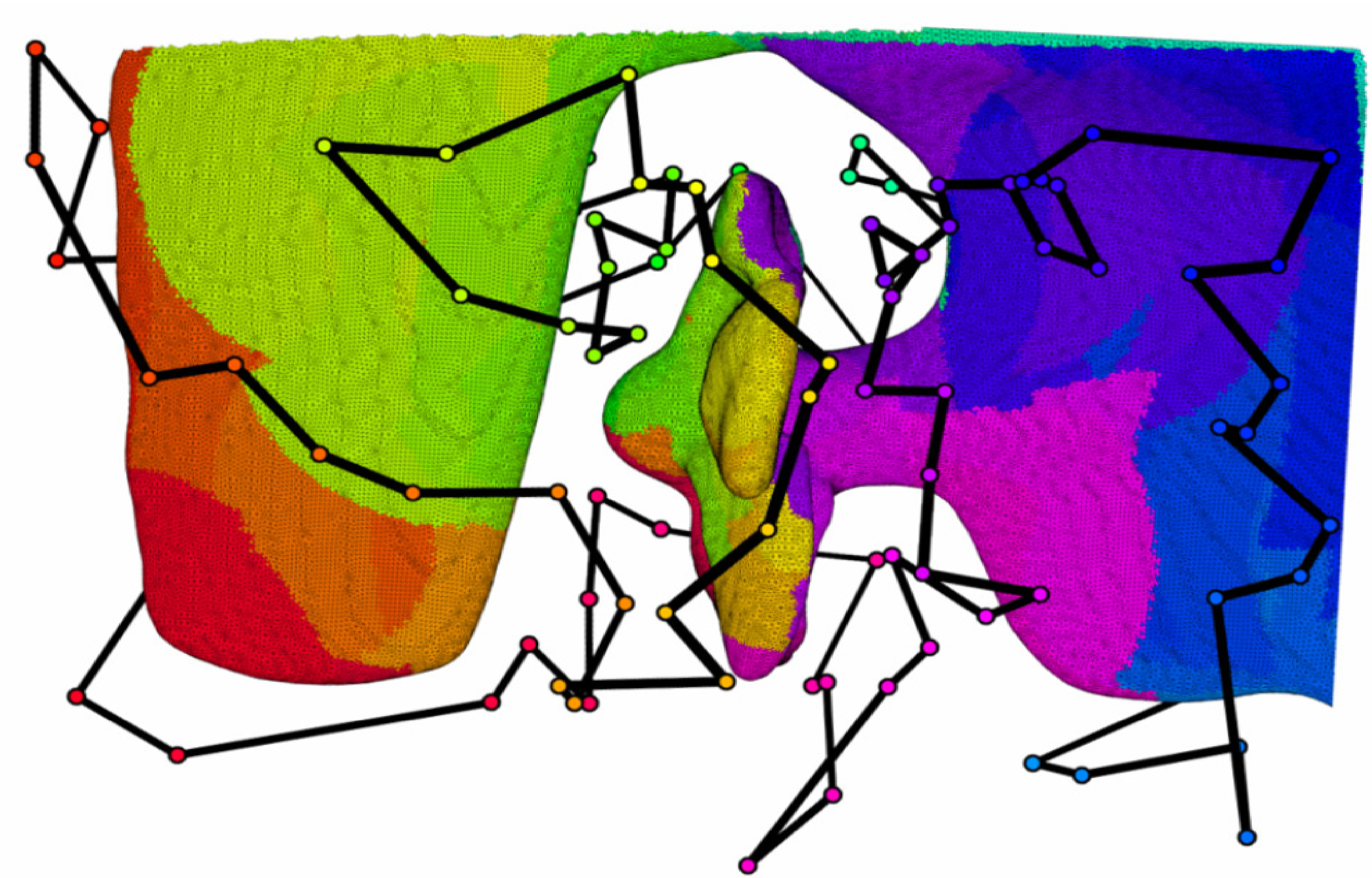
- Watchman route algorithm and redundant roadmap algorithm are probabilistically complete, as long as $\varepsilon > 0$ whenever $\delta > 0$
- For these algorithms, $A \subseteq \mathcal{Q}$ is a set containing all areas where the robot sensor footprint intersects at least one geometric primitive, so this condition is always satisfied
- Sampling on a reduced-dimensional manifold (a series of 2D slices in a 2.5D algorithm, for example) may yield a case in which $\mu(S_i \cap A)/\mu(A) = 0 \; \exists S_i \in \mathcal{S}$ even though $\mu(S_i)/\mu(\mathcal{Q}) > 0 \; \forall S_i \in \mathcal{S}$
- Gives more appealing convergence than the geometry-theoretic alternative: for 1 million primitives, $\varepsilon > 0.001$, $k = 10$, probability of failure plunges from large to infinitesimally small between 10^4 and 10^5 samples

Overall Outcome of Analysis

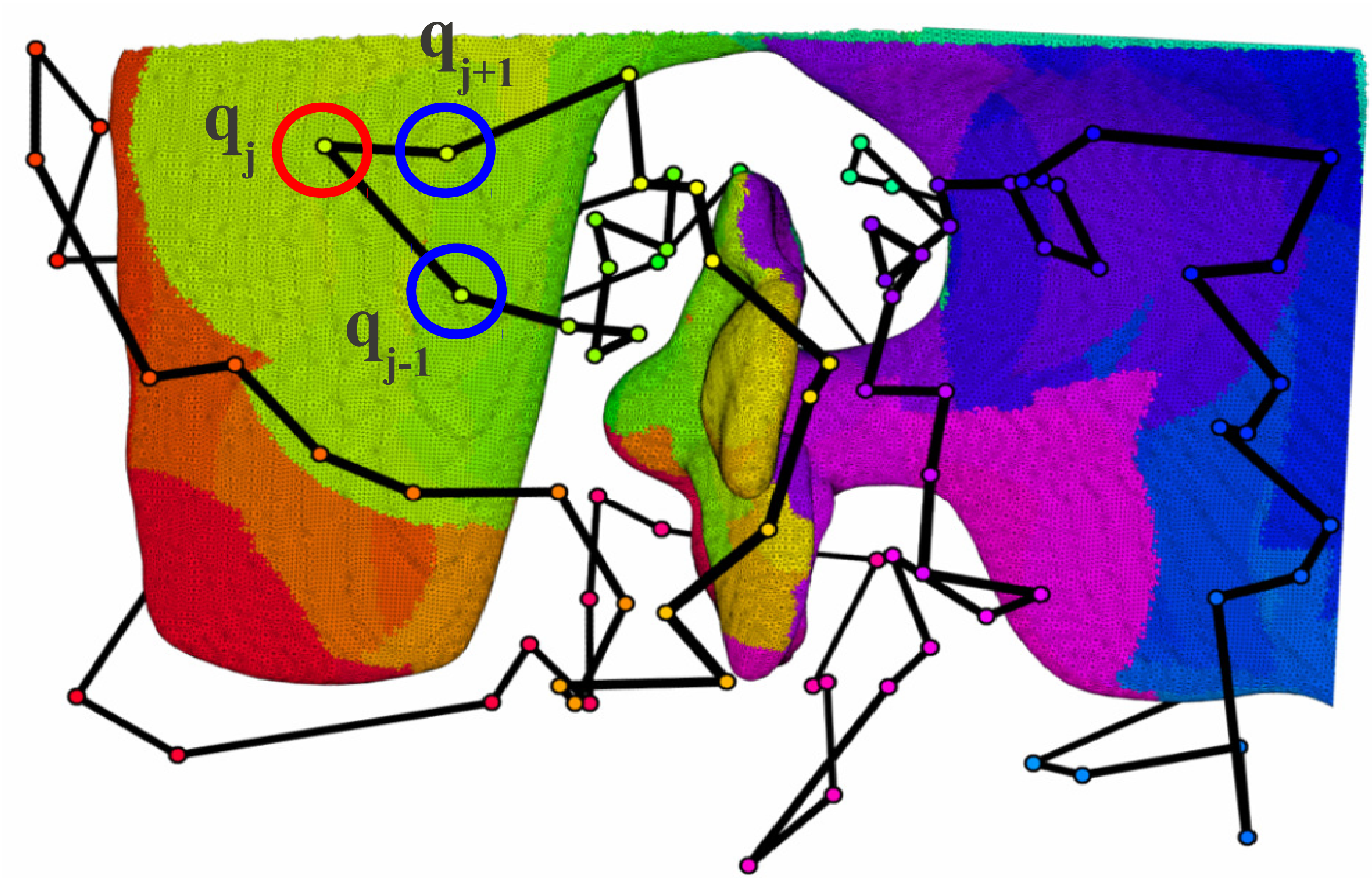
- View planning routines of watchman route algorithm and redundant roadmap algorithm are probabilistically complete
- Multi-goal planning routines of both algorithms also probabilistically complete
- In all cases, convergence bounded by decaying exponential in number of samples drawn
- Full, integrated algorithms fail to converge only when a “prison cell” is present



An Initial Feasible Inspection Route: Room For Improvement

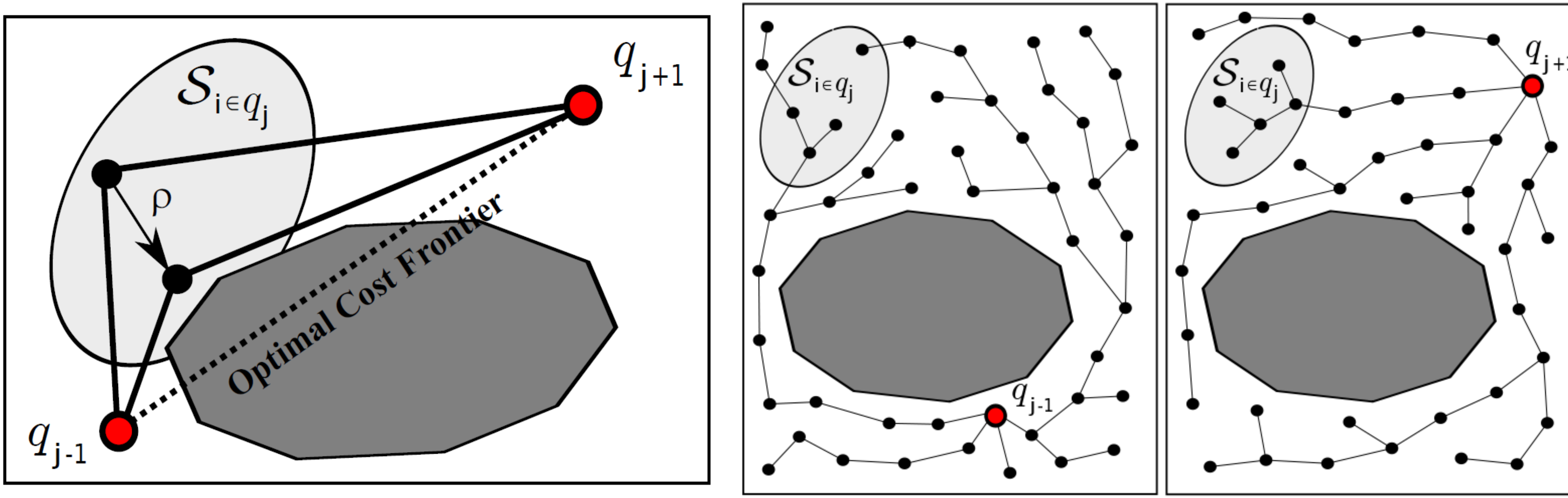


An Initial Feasible Inspection Route: Room For Improvement



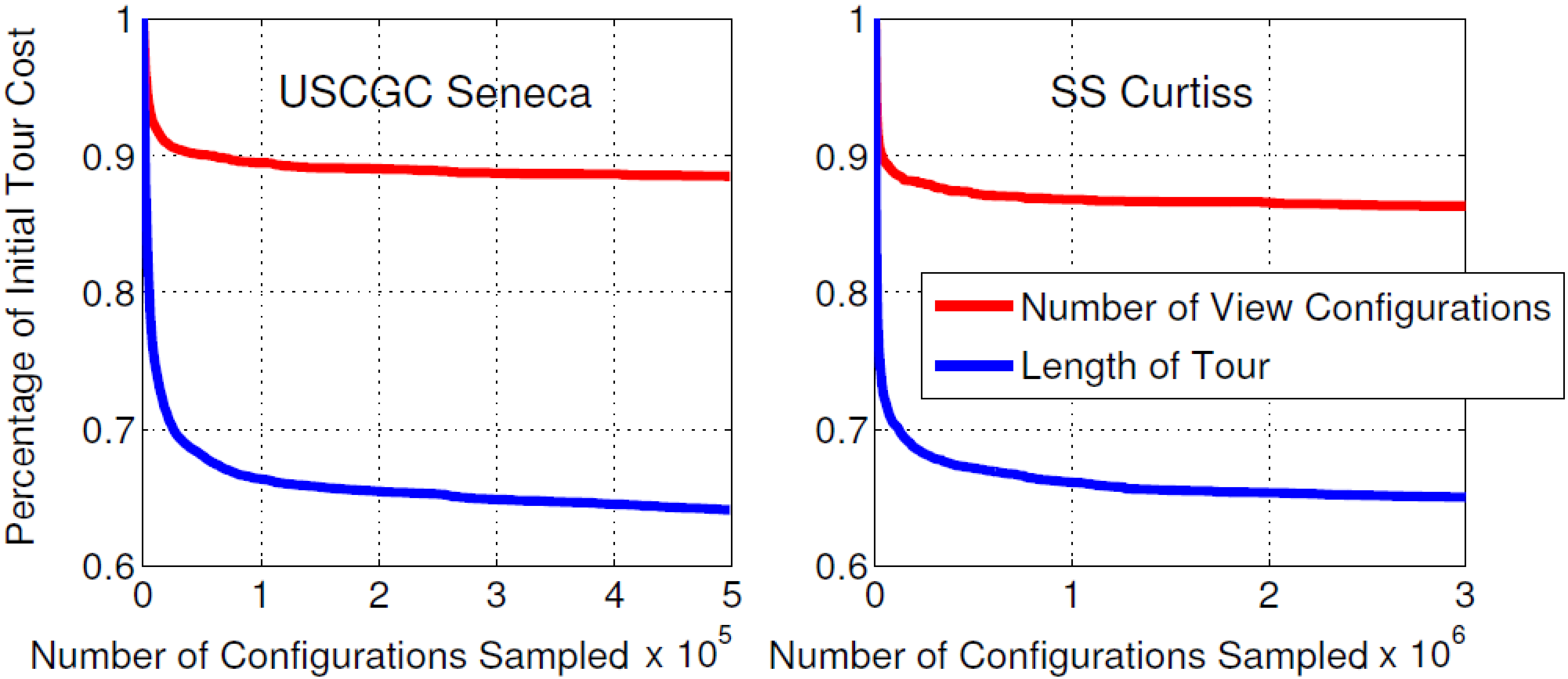
Adjust the position of a view configuration relative to its two neighbors

Procedures for Local Smoothing



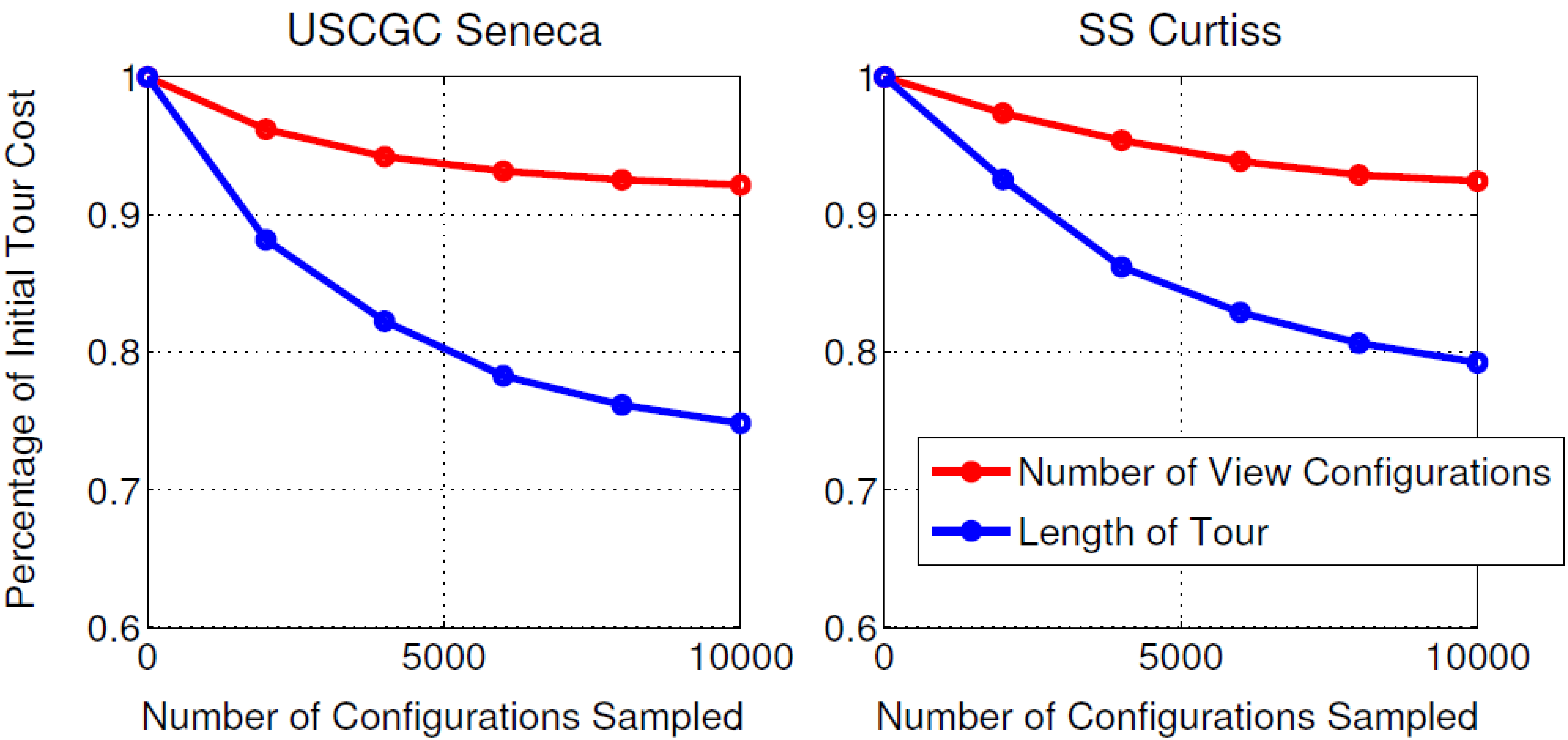
- Ship hulls are expansive, contiguous structures, and the HAUV has a small FOV: view configurations are densely packed
- Attempt to connect view configurations using straight-line paths, and project them to the frontier of (local) optimal cost
- If views cannot be bridged by straight-line paths, a parallel implementation of the RRT* algorithm (Karaman & Frazzoli 2011) can be used instead to find paths optimal in length in the limit

Algorithm Performance over Two Hours



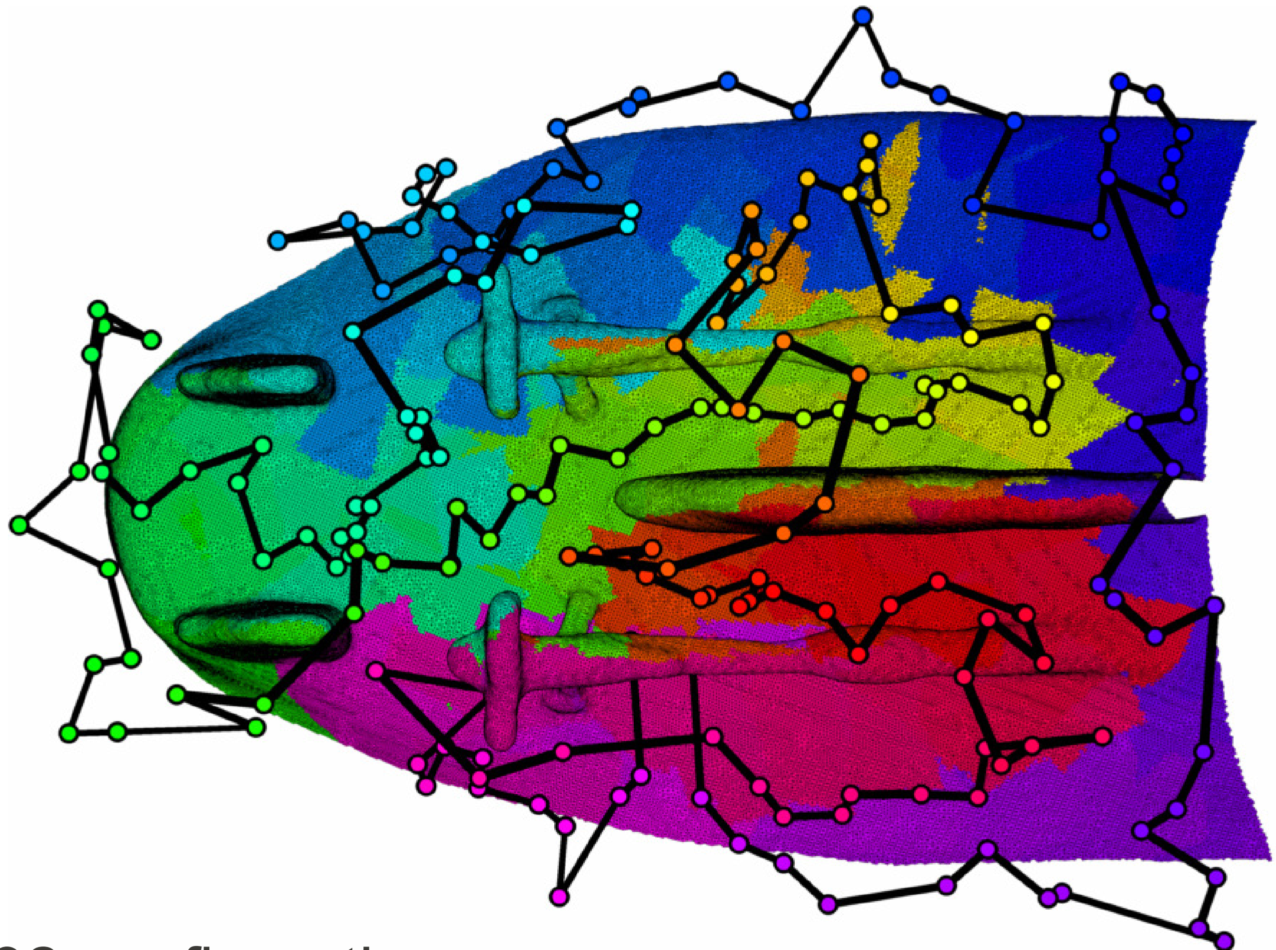
- Performed on Dell Precision w/ 3.20 GHz Processor, 24 GB RAM
- The two ships achieved different worst-case quantities of samples over the allotted computation time, mean of 25 trials is represented

Zooming In: The First 10,000 Samples



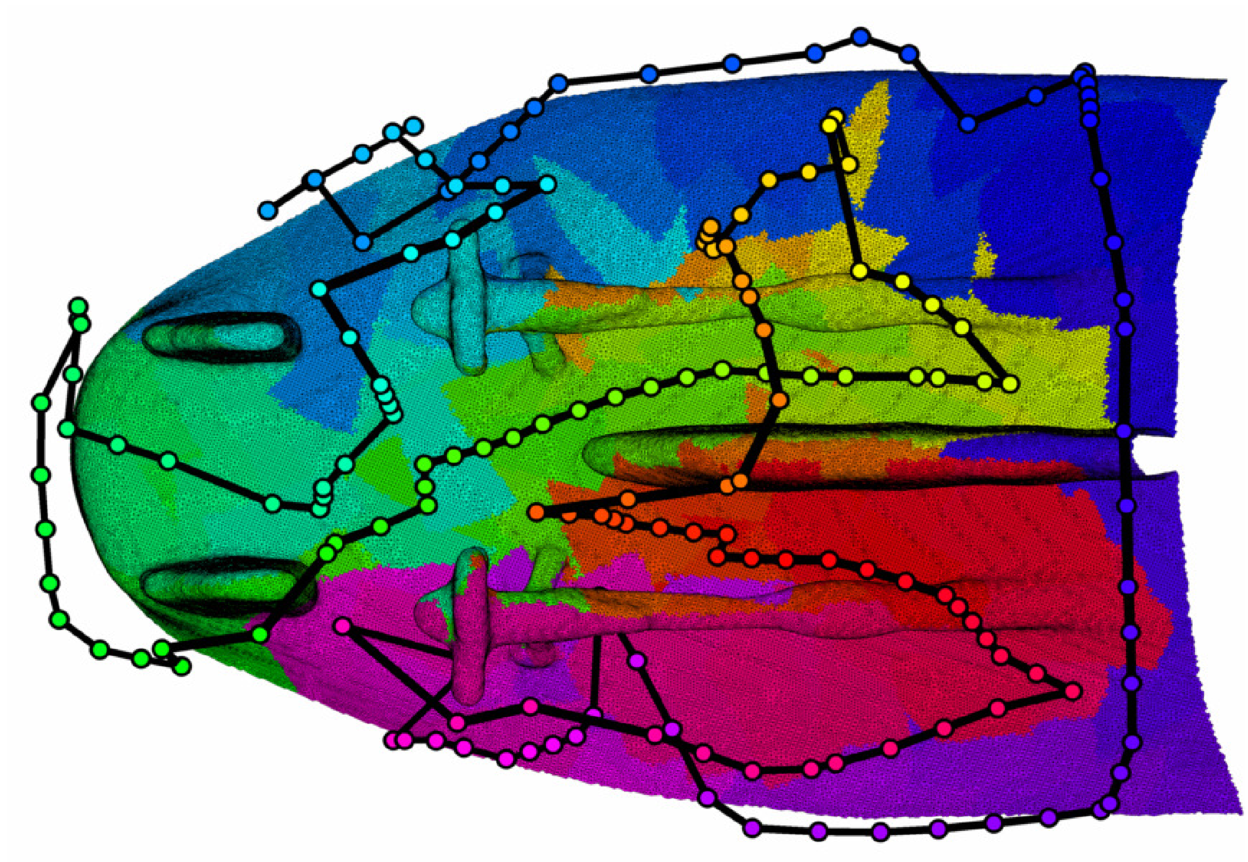
- The first 1-2 minutes of sampling were highly productive

USCGC Seneca Inspection Route



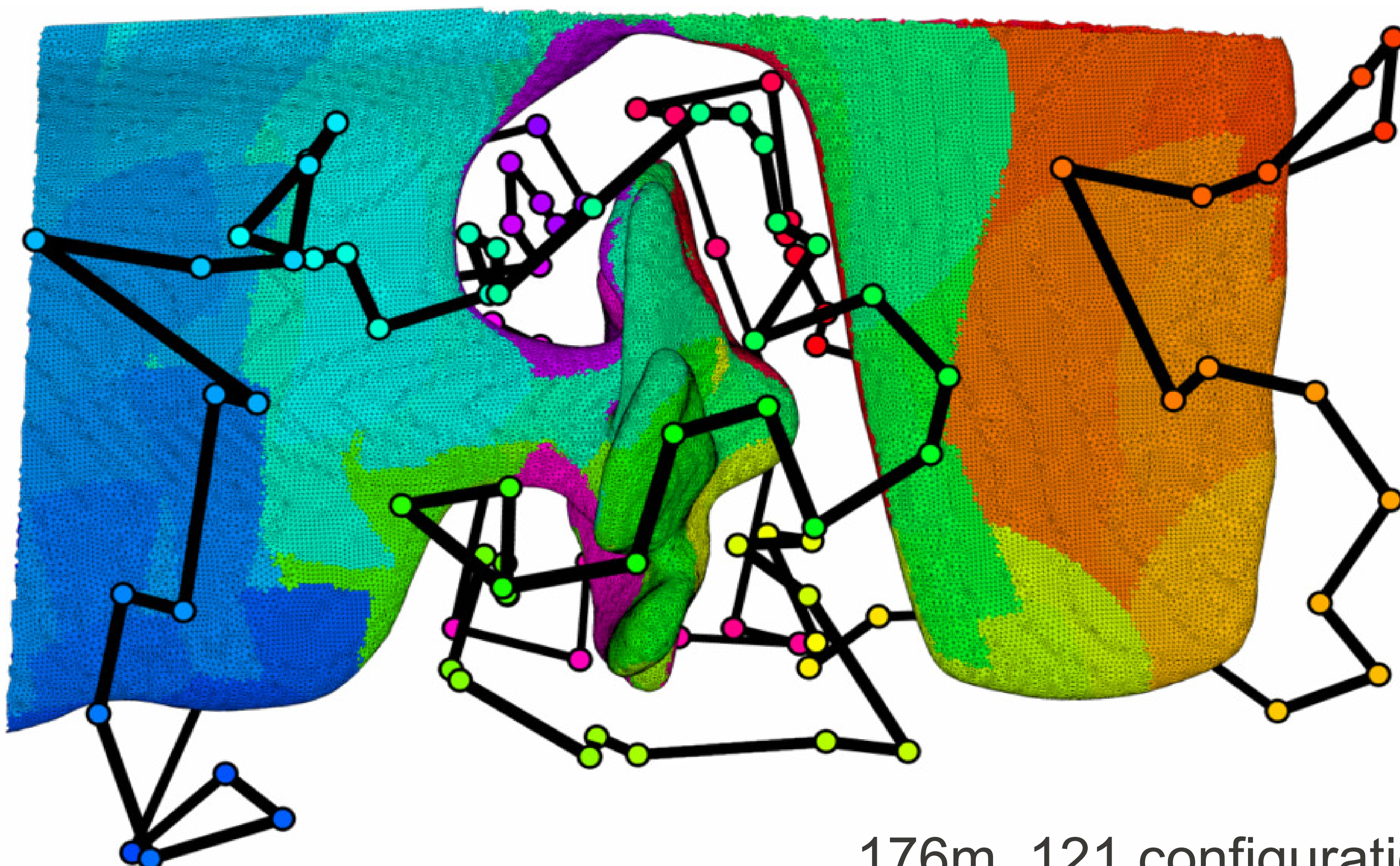
246m, 192 configurations

USCGC Seneca Inspection Route



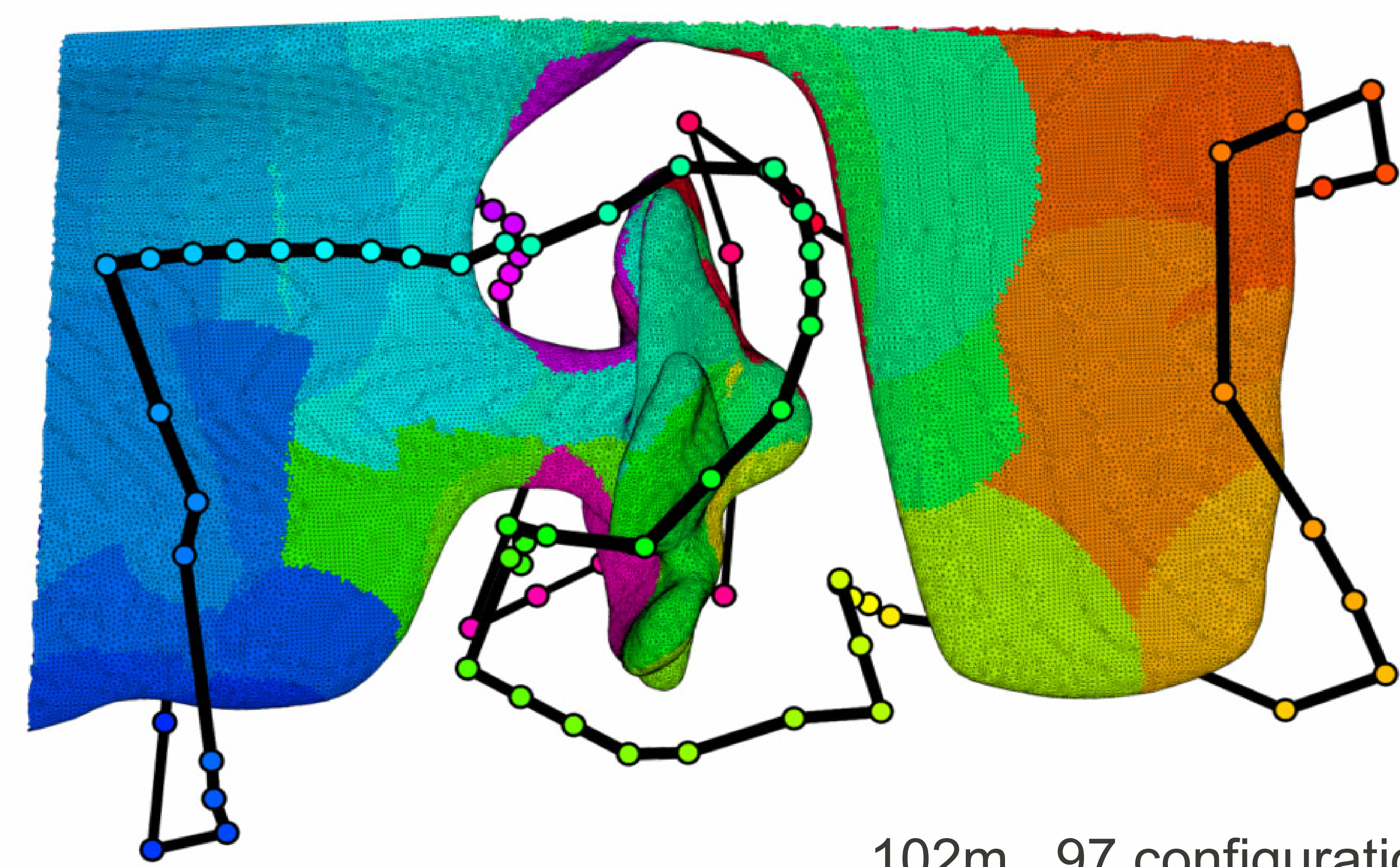
157m, 169 configurations

SS Curtiss Inspection Route



176m, 121 configurations

SS Curtiss Inspection Route

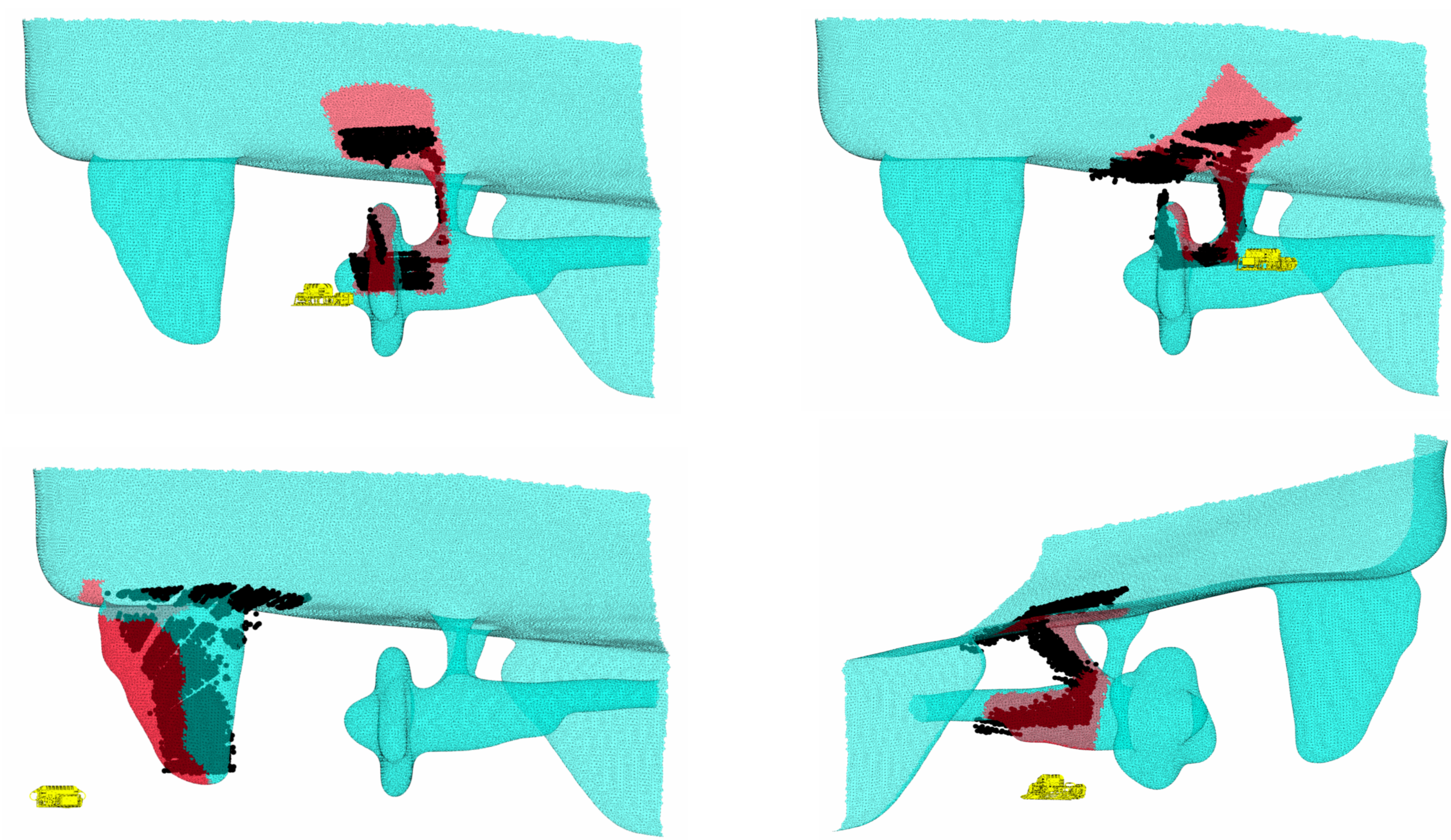


102m, 97 configurations

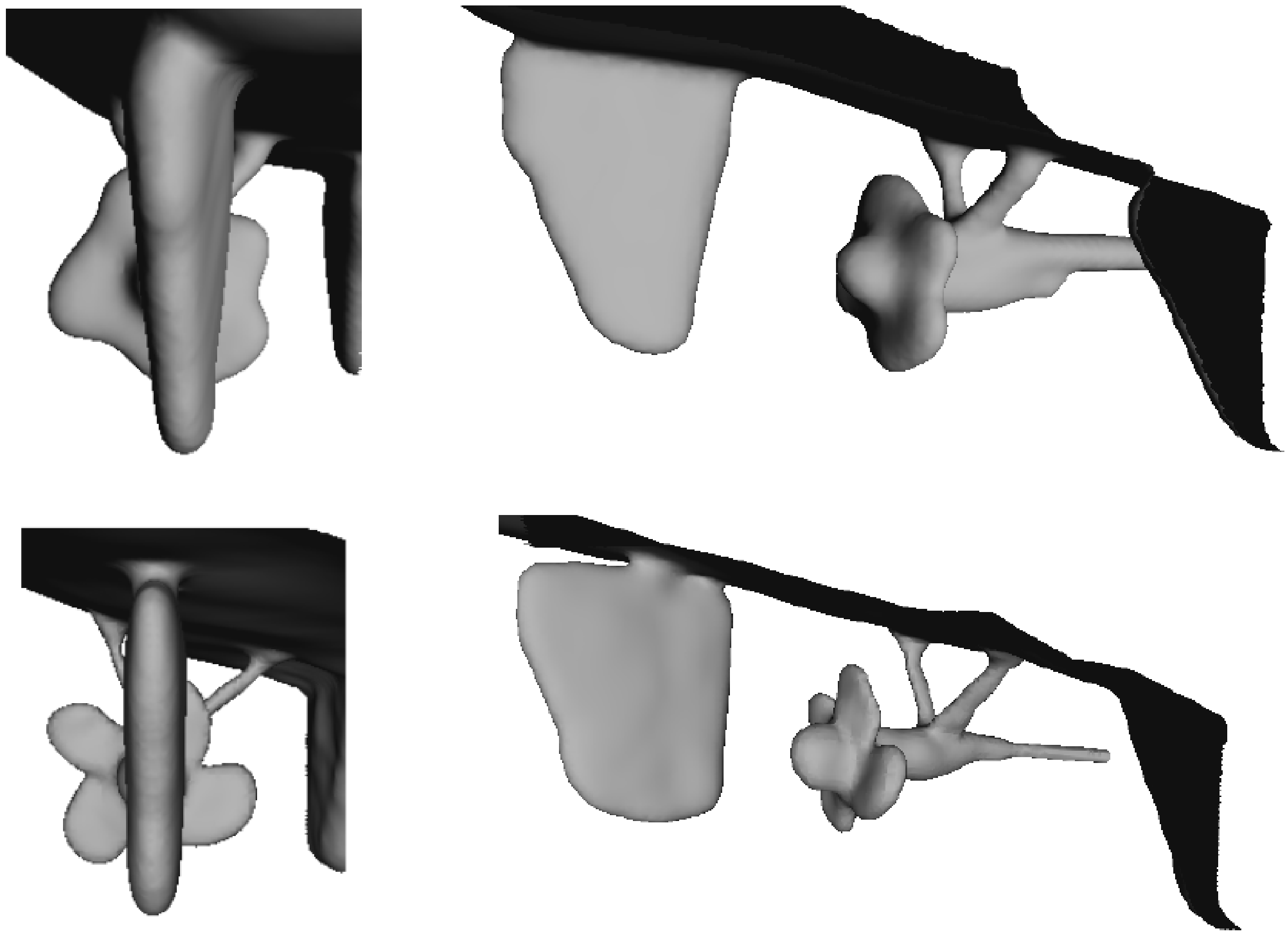
Field Deployment of HAUV

USCGC Seneca Feb. 2012, executed path planned using *a priori* model

Data Collected from Planned Sensor Views



Improved-Resolution Mesh Obtained from Planned Inspection



Conclusions

- We have proposed a comprehensive methodology for the **sampling-based** design and analysis of geometric inspection routes
- The first probabilistic completeness analysis applied to robot coverage path planning
  - Unites concepts in path planning and sensor placement methods
  - Discrete coverage perspective broadens applicability of analysis tools
- New improvement algorithm that iteratively shortens feasible coverage routes
- Recent Experimental Field Implementation of Algorithm
- **Future work:** Anytime algorithms in an adaptive in-water inspection, integrated localization, mapping, and planning, and extension to multi-agent inspection scenarios for colossal structures

Acknowledgments

- **ONR:** Dr. Tom Swean, Victoria Steward (Grant N00014-06-10043)
- **MIT Colleagues:** Dr. Michael Kaess, Hordur Johannsson, Prof. John Leonard, Prof. Daniela Rus, Prof. James Orlin, Prof. Doug Hart
- **UMich Colleagues:** Prof. Ryan Eustice, Ayoung Kim, Paul Ozog
- **Bluefin Robotics:** Dr. Jerome Vaganay, Kim Shurn, Mike Elkins
- **SeeByte Ltd.:** Dr. Jose Vasquez and Dr. Scott Reed

Questions?