Real-Time Planning Under Uncertainty for AUVs Using Virtual Maps

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SCAN ME

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Motivation

Reliable localization is an essential capability for marine robots navigating in **GPS-denied** environments.

PROBLEM

➔ SLAM, commonly used to mitigate dead reckoning errors, still fails in **feature-sparse** environments or with **limited-range** sensors.

➔ Performing belief propagation is **computationally costly**, especially when operating in **large-scale** environments.

GOAL

Provide a planning framework that:

➔ Deals with the **feature-sparsity** of **large-scale** environments.

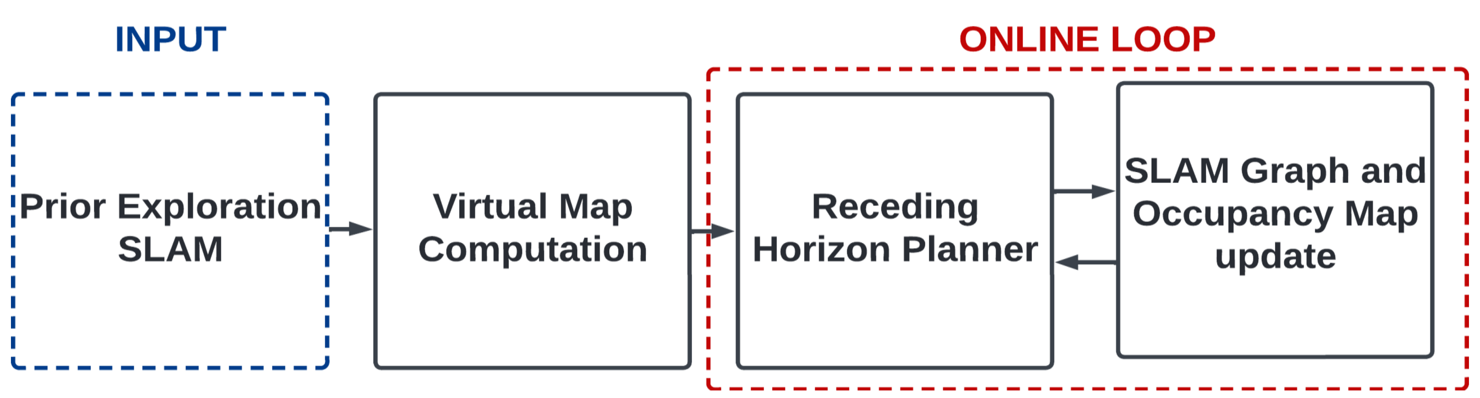
➔ Eliminates the need for belief propagation at each time step for **computational efficiency.**

➔ Suitable for platforms running in **real-time.**

➔ Successfully accommodates **imperfect prior information**.

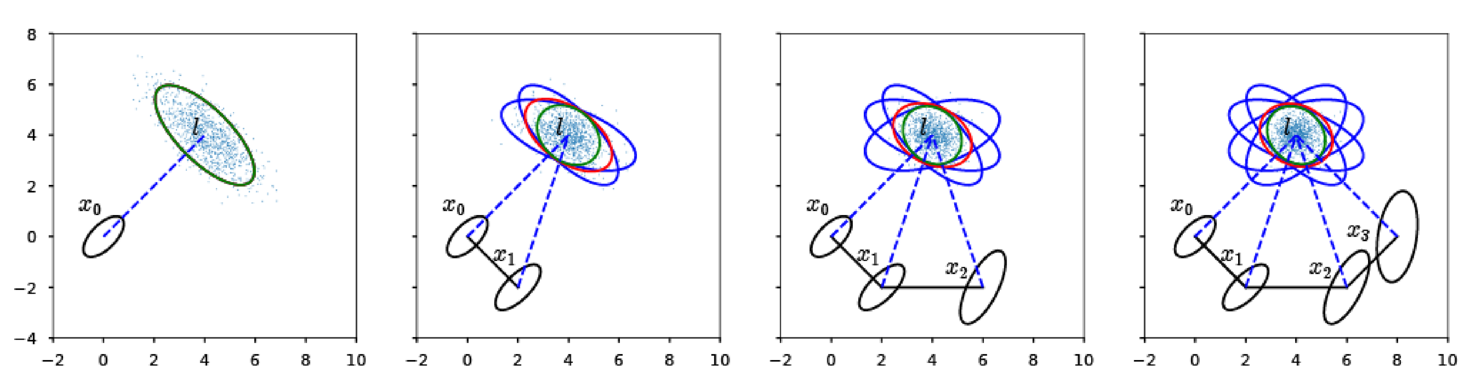
Methodology

General pipeline for planning under uncertainty framework.



VIRTUAL MAP VALUES

Grid cell covariances derived from measurements collected at specific poses.



Covariance intersection is used to approximate map cell uncertainty.

Grid cell covariances are used for **belief space planning**.

VIRTUAL MAP

➔ **Utility costmap** for our path planning strategy.

➔ **Avoids the computationally expensive** belief propagation at each timestep common to most planning under uncertainty strategies

➔ Helps **incorporate uncertainty** for localization accuracy.

RECEDING HORIZON PLANNING

➔ **Continuous feedback** from the environment.

➔ Helps **attenuate errors** in tracking and perception.

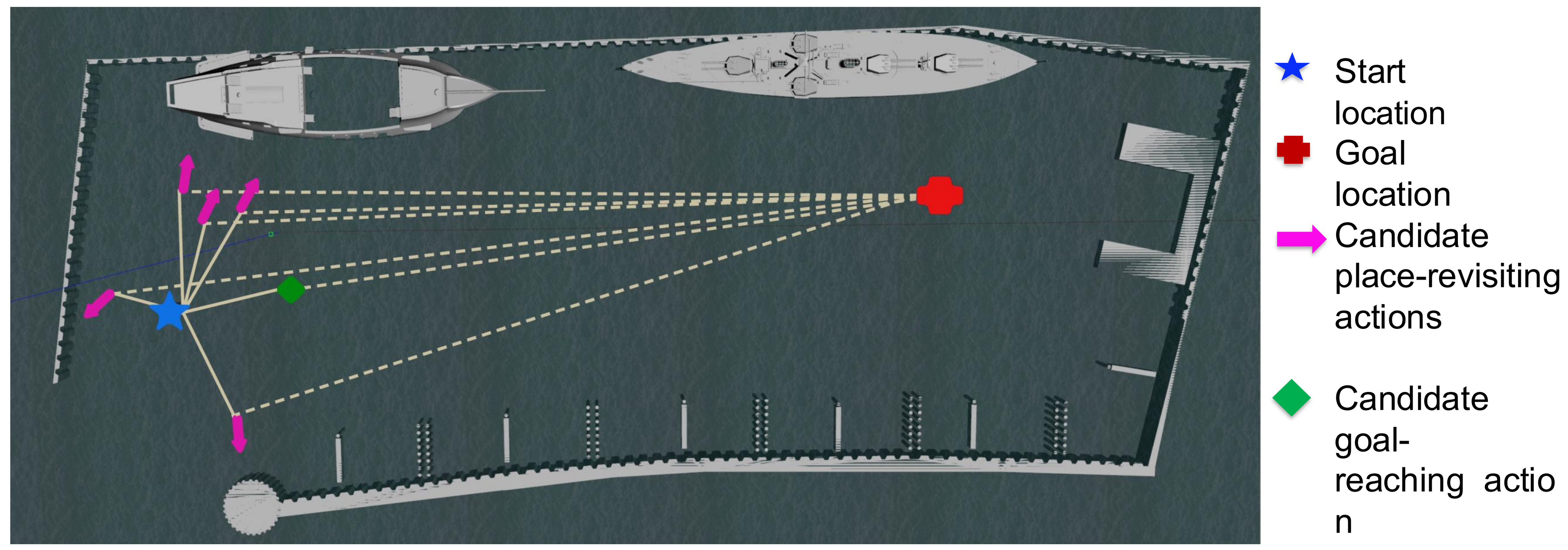
Candidate Actions ➔ Utility computation ➔ Action selection

Action types:

➔ **Place revisiting:** lower uncertainty.

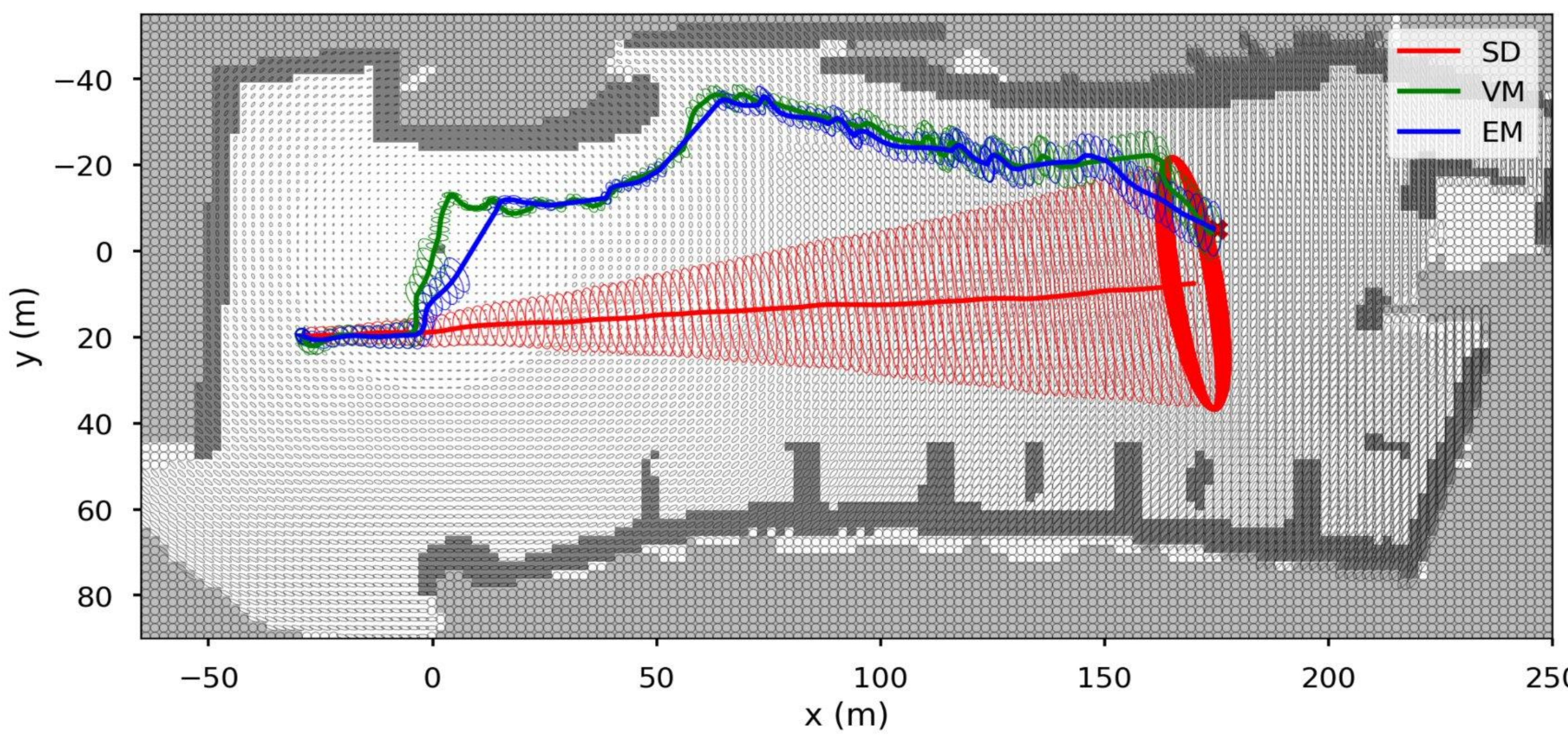
➔ **Shortest Distance**: reach final goal..

Receding Horizon Path Planning



Experiments

Our Virtual Map (VM) approach vs. Shortest Distance (SD) and Expectation-Maximization (EM)



➔ **SD planner:** shortest viable path to the goal.

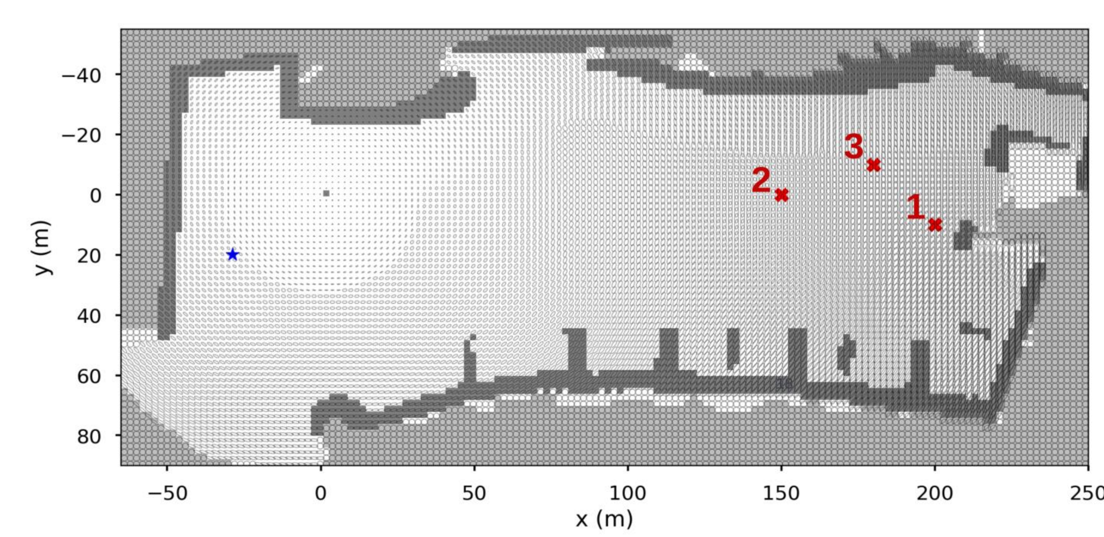
➔ **Our planner** uses receding horizon planner and employs Virtual Map as cost map for planning.

➔ **EM planner** uses receding horizon planner and employs full EM belief propagation.

Experiments were executed using a **high-fidelity Gazebo AUV simulation.**

- The simulated vehicle was equipped with an imaging sonar, an IMU, a DVL, and a pressure sensor.
- Three environments were designed: a marina, an offshore fish farm, and a bridge-tunnel system.
- As a preprocessing step, each environment was fully explored while performing sonar SLAM.
- Each scenario has one start location and three different goal locations.
- Each run consisted of the robot navigating from a start to a goal location, and was repeated for 100 trials. The results shown are the average values of all the trials executed.

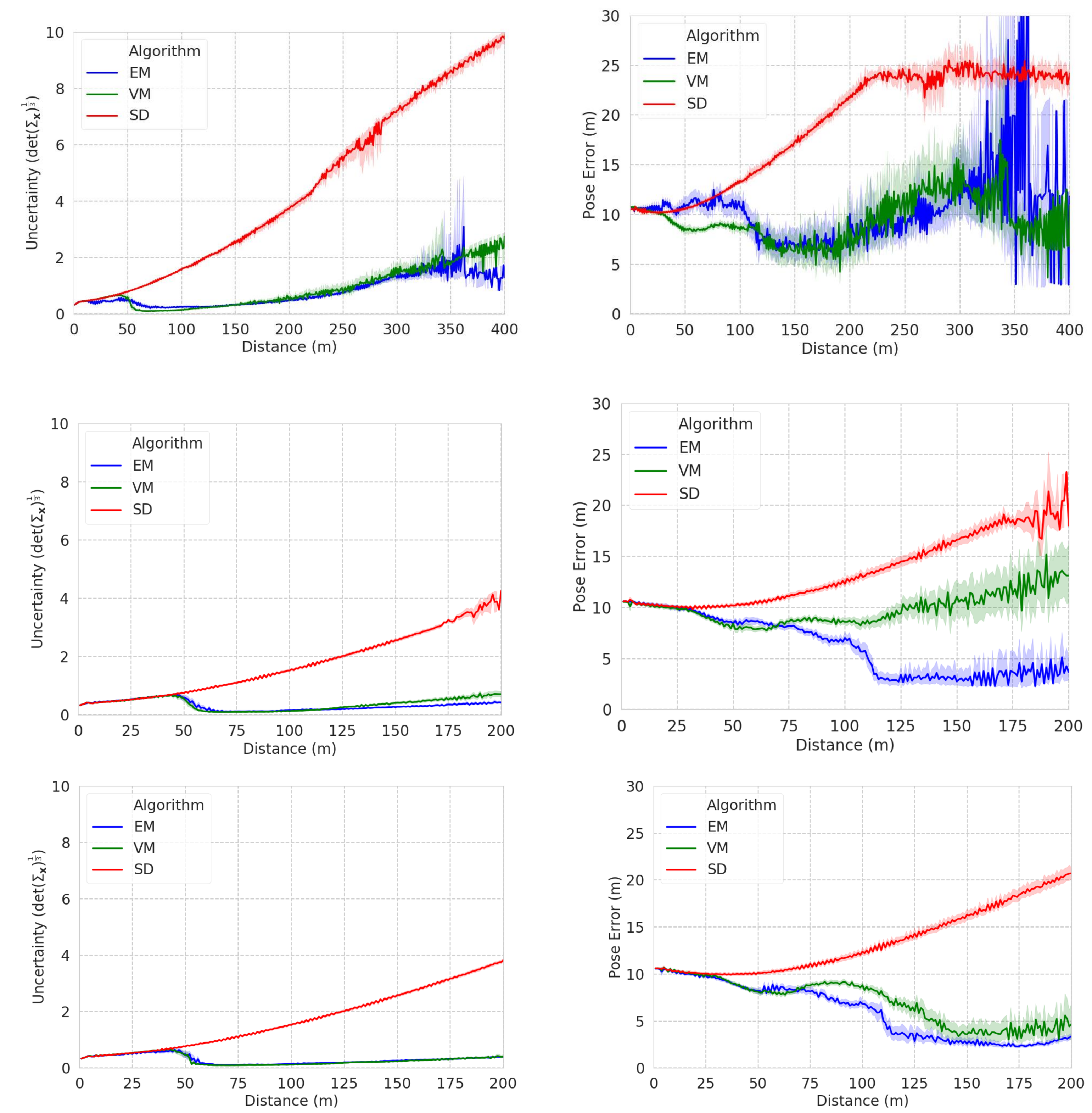
**Only results for the Marina Environment are shown here*



Start location and end goals for the Marina Environment

Results

Goals 1, 2, 3 shown top to bottom



Time required for utility evaluation in each experiment

	Computation Time (sec)					
	EM		VM		SD	
	(μ)	(σ)	(μ)	(σ)	(μ)	(σ)
Marina 1	3.3553	0.1446	0.0041	0.0001	0.0015	0.0002
Marina 2	2.9324	0.0598	0.0039	0.0002	0.0014	0.0002
Marina 3	3.1507	0.1396	0.0040	0.0001	0.0015	0.0004

Conclusion

Results show a decrease in uncertainty and pose error compared to a standard shortest-distance approach. Furthermore, our approach is much faster than full belief propagation, while still maintaining low uncertainty and pose error.

Potential improvements include:

➔ Extending this strategy to 3D planning scenarios.

➔ Performing virtual map updates to accommodate important changes in the environment.

Acknowledgements

This research was supported by NSF Grant IIS-1652064 and USDA-NIFA Grant 2021-67022-35977