

# Informative Trajectory Planning for Search and Capture of Drifting Targets with ASVs

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## Introduction

Maritime search and capture operations are critical for both search and rescue and environmental cleanup. Specifically, timely mapping and subsequent collection of floating pollutants, such as plastic litter, are essential to protect marine life. To advance these efforts, this study presents a sampling-based trajectory optimisation approach for search and capture of moving targets with autonomous surface vehicles (ASVs).

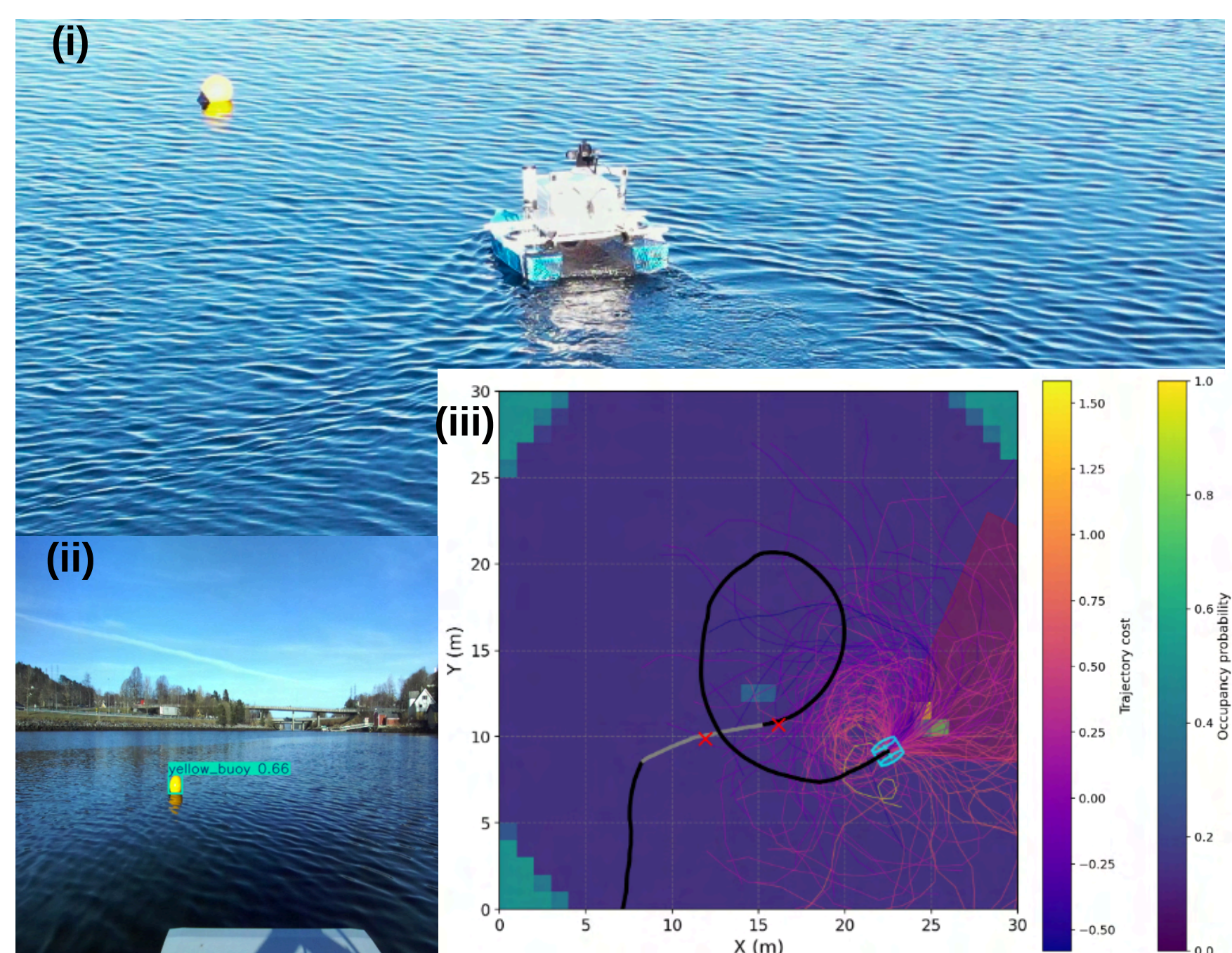
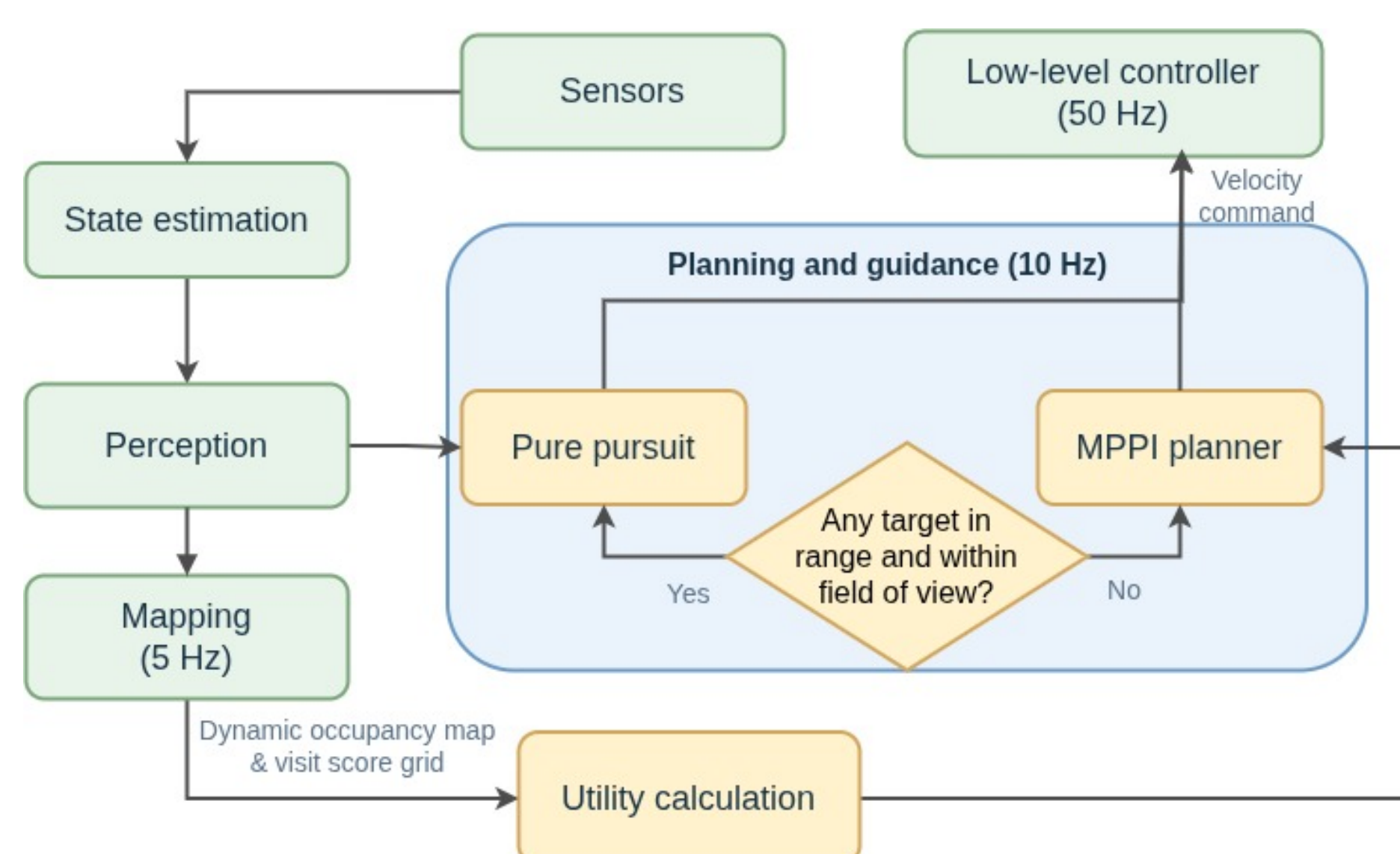


Figure: (i) Field tests with an ASV; (ii) Camera onboard the vehicle used for object detections; (iii) Plot with occupancy map, also showing the path followed by the ASV and the MPPI rollout trajectories.

## Approach



We use an ASV equipped with an onboard stereo camera for object detection and mapping. A dynamic occupancy grid map is used to map target positions, following [1]. Drift predictions are estimated based on [2]. We also maintain another occupancy grid  $\mathcal{V}$  that stores a visit score which captures the time-varying uncertainty in the map. It is updated as follows:

$$v_{i,j} = \begin{cases} 0 & (i,j) \in \mathcal{F}^t \\ \min(v_{i,j} + \lambda \Delta t, 1) & (i,j) \notin \mathcal{F}^t \end{cases} \quad (1)$$

We develop a spatiotemporal informative planning approach based on model predictive path integral (MPPI) control [3]. We use a hybrid planning approach and switch to a pure pursuit guidance strategy to intercept the target once the vehicle is within a certain radius threshold  $r_d$  of a target and in field of view. The cost for planning is computed as:

$$J = \sum_{t=1}^T \gamma^t (C^t) \quad (2)$$

$$C^t = a_1 C_e^t + a_2 C_t^t + a_3 C_p^t + a_4 C_c^t,$$

where the trajectory cost  $J$  is the discounted sum of per-timestep costs  $C_t$  over the planning horizon  $T$ . The exploration and tracking costs are given by  $C_e^t$  and  $C_t^t$ ;  $C_p^t$  and  $C_c^t$  are path and collision costs.

**Exploration cost** rewards trajectories that reduces uncertainty in  $\mathcal{V}$ :

$$C_e^t = -\frac{1}{HW} \sum_{(i,j) \in \mathcal{F}^t} v_{i,j} \quad (3)$$

**Target tracking cost** rewards trajectories that reduce distance and bearing to predicted target occupancy regions, aided by spatiotemporal target predictions  $\hat{P}$  [1]:

$$C_t^t = - \sum_{(i,j) \in \mathcal{F}^t} \hat{P}^t(i,j) e^{(-c_1 d_{i,j}^2 - c_2 \theta_{i,j}^2)} \quad (4)$$

**Path cost** promotes speeds closer to the desired speed and penalises high yaw rates.

$$C_p^t = (\bar{u}^t - \bar{u}_d^t)^2 + (\bar{r}^t)^2 \quad (5)$$

**Collision cost** adds a soft barrier function to avoid collisions and prevent the vehicle from going out of the navigable region:

$$C_c^t = \log(1 + e^{d_s - d_{min}}) \quad (6)$$

For sampling trajectory generation in MPPI, the optimal control sequence is perturbed with added noise. In this work, we modify the sampling distribution by adding a time-correlated noise using the Ornstein-Uhlenbeck process instead of uncorrelated Gaussian noise that is generally used. This is done to generate a more diverse set of trajectories.

## Simulation Results

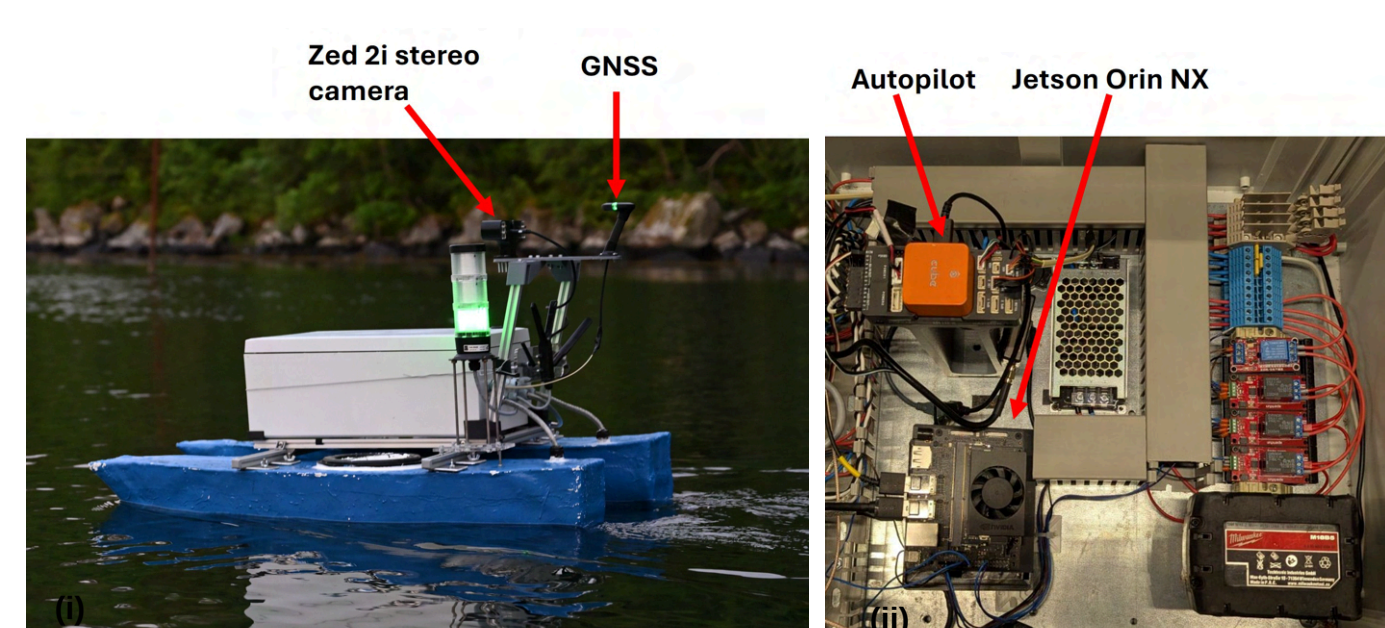


Figure: (i) Field deployment of ASV; (ii) Simulations environment for search and capture of drifting targets.

We perform simulations with the Virtual Robot-X (VRX) simulator over a 100 m  $\times$  100 m search area with 10 targets distributed randomly, for a maximum duration of 180 s or until all targets are captured. We compare our proposed planner against baselines over ten Monte-Carlo simulations:

| Planner          | No. captures   |
|------------------|----------------|
| MPPI             | 9.2 $\pm$ 1.48 |
| Receding horizon | 5.4 $\pm$ 1.17 |
| Frontier-greedy  | 6.1 $\pm$ 1.79 |

## Experimental Setup



We conduct field experiments with a 1.2 m long catamaran ASV. It is equipped with a Cube Orange autopilot for velocity control, and our framework is implemented with ROS2 on a Jetson Orin NX. The control commands output from the hybrid planner to the autopilot is velocity command in surge speed ( $u$ ) and yaw rate ( $r$ ).

## Field Tests

We perform search and capture of three buoy markers used as targets, over a 900 m<sup>2</sup> search area in a strait. The targets freely drift under the influence of moderate current and wind during the tests. The desired vehicle speed is set to 0.5 m/s, and each trial lasts for a duration of 120 s. The results from four runs are summarised:

|         | No. captures | Time taken |
|---------|--------------|------------|
| Trial 1 | 2/3          | —          |
| Trial 2 | 3/3          | 95 s       |
| Trial 3 | 3/3          | 61 s       |
| Trial 4 | 3/3          | 49 s       |

We also show plots from various instants of a single trial. Video attachments from the field tests are available in the link in the [QR code](#).

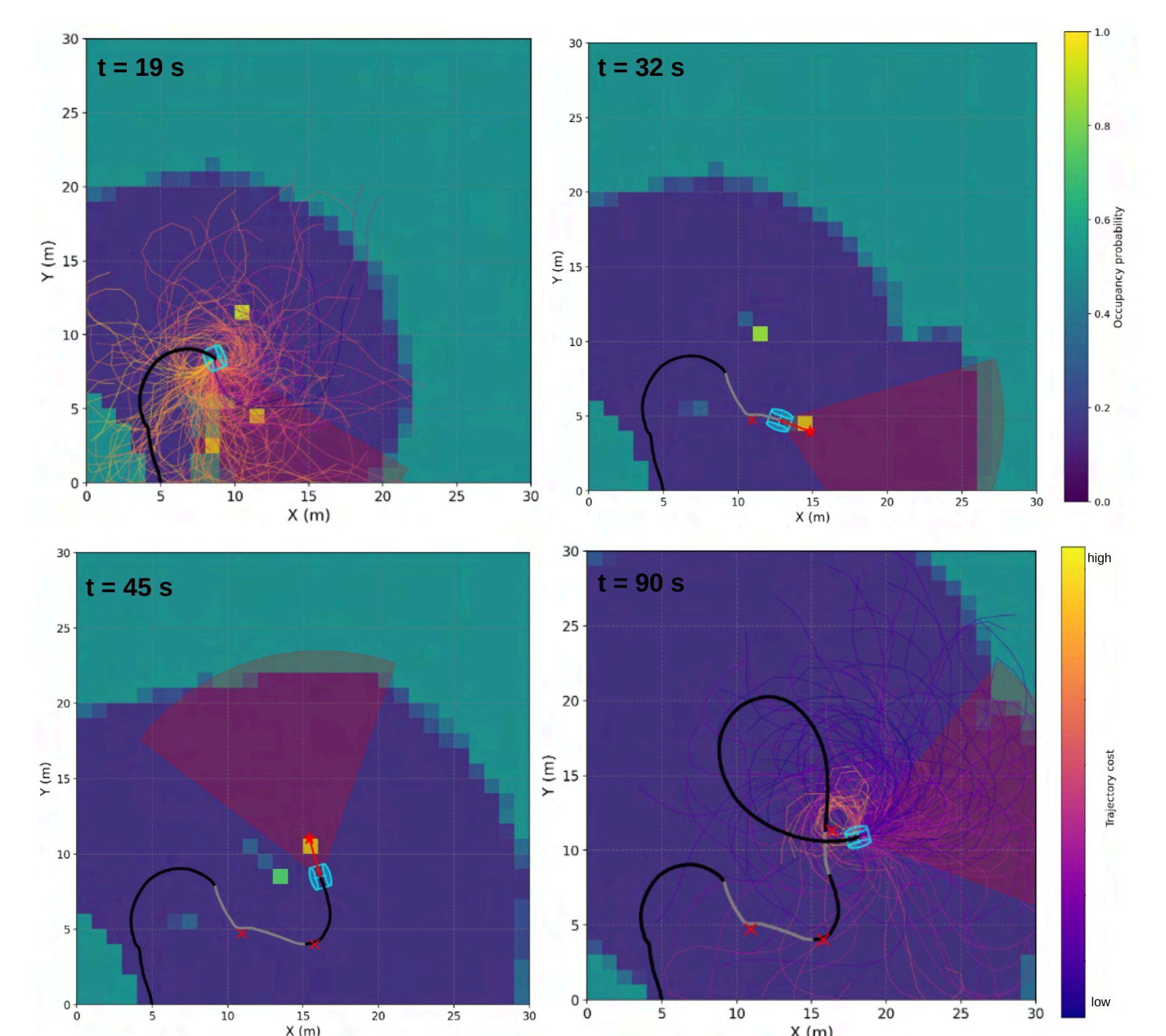


Figure: The ASV successfully intercepts all three targets. Black and grey segments denote portions of the path where the vehicle is in exploration and interception modes, respectively.

Only one target is missed across all trials, demonstrating the effectiveness of our MPPI planner for search and capture of moving targets.

## Lessons Learnt and Future Work

- **Better estimation of drift:** Our mapping approach relies on wind measurements for estimating drift. Inaccurate mapping in absence of reliable measurements also affects planning.
- **Multirobot monitoring for improved efficiency:** While our approach performs well with a single robot in unobstructed search areas, it can be challenging in large or cluttered spaces.

## References

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- [3] G. Williams, N. Wagener, B. Goldfain, P. Drews, J. M. Rehg, B. Boots, and E. A. Theodorou. Information theoretic mpc for model-based reinforcement learning. In *ICRA*, 2017.

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