

Into the Uncharted with Confidence: Online System Identification for Driving on Unseen Terrains



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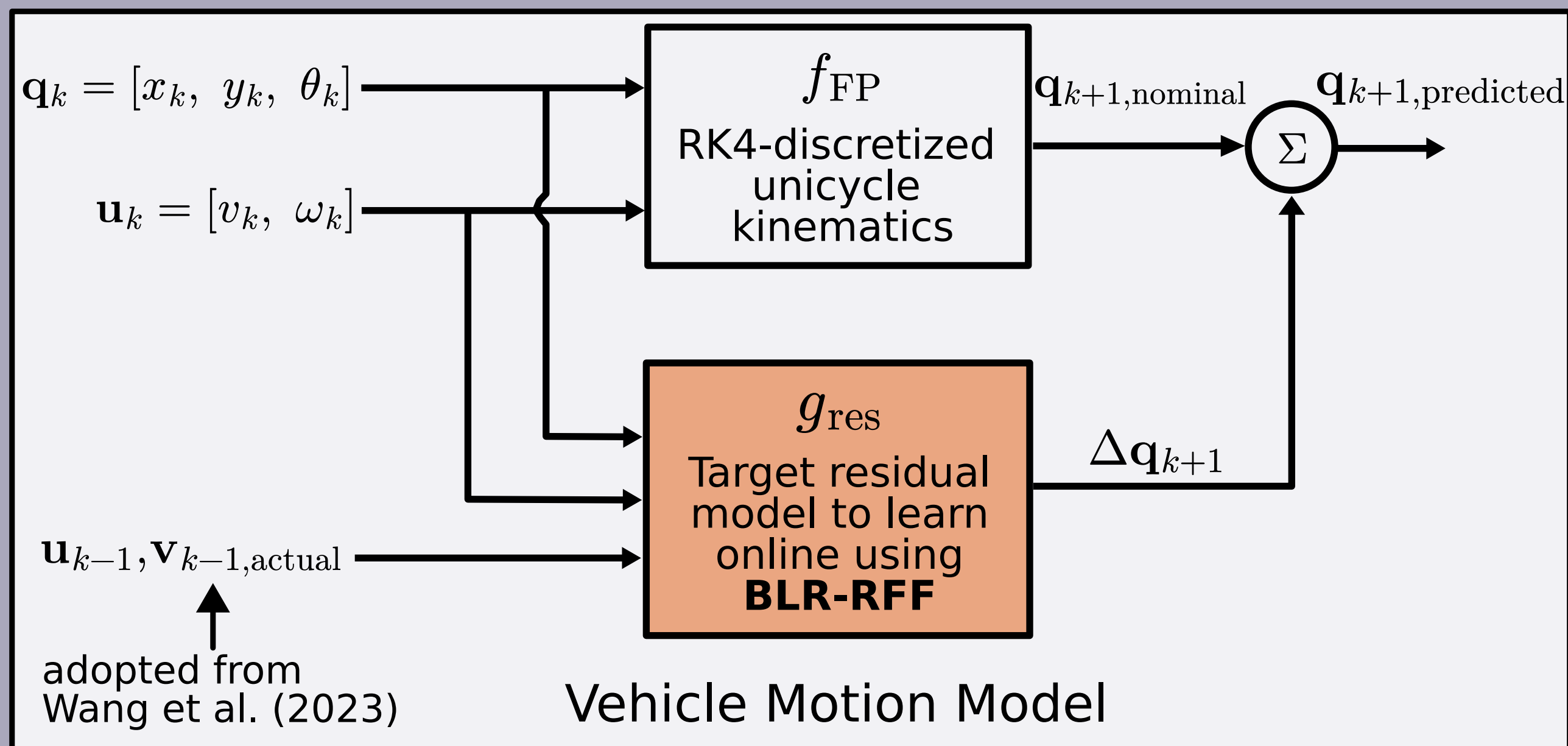
I. About This Poster

In this poster, we propose a **recursive system identification approach** for Uncrewed Ground Vehicles (UGVs) driving on **unseen challenging terrains** with prior from a standard baseline terrain.

Our Contributions

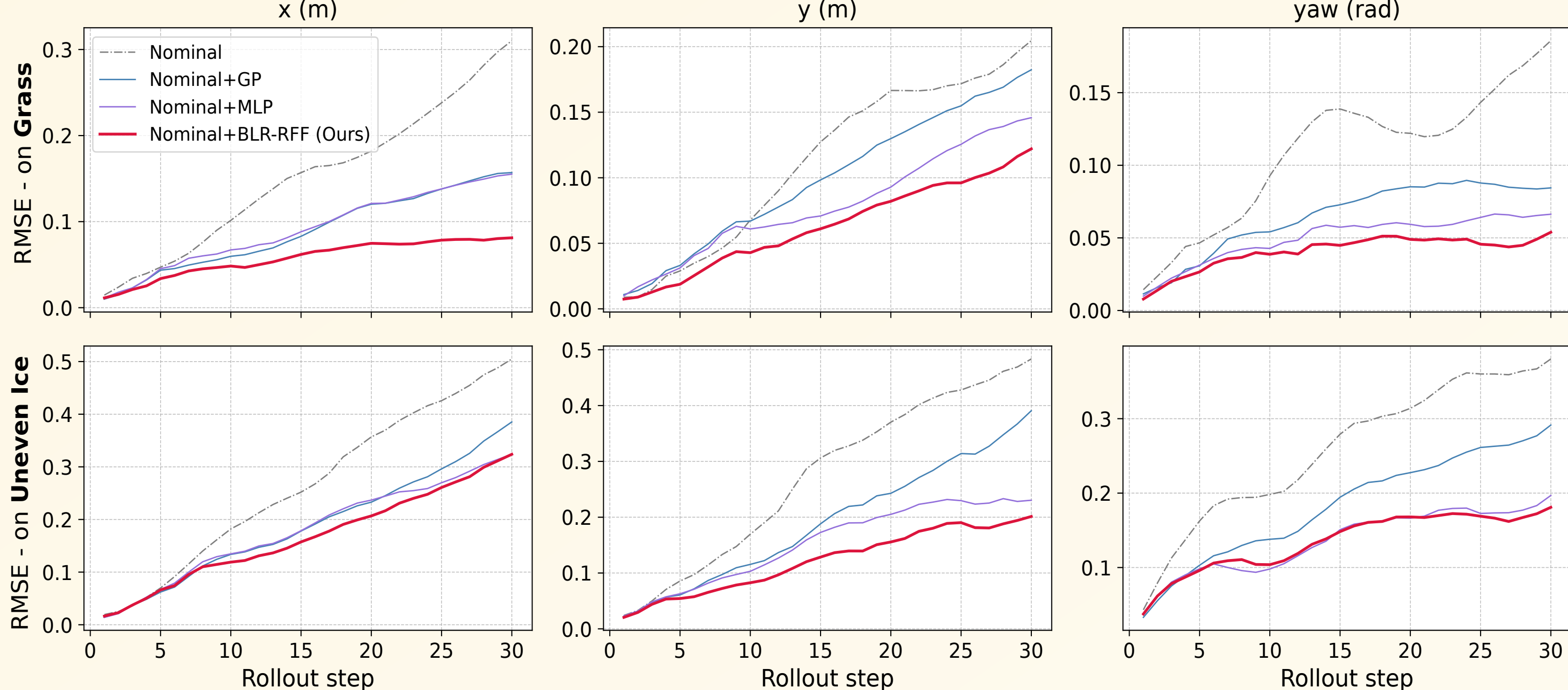
- Our approach, **BLR-RFF** (Bayesian-Linear-Regression-updated Random Fourier Features), applies Bayesian linear regression to learn RFF weights for residual dynamics in a recursive manner, leveraging a baseline terrain prior to generalize to unseen terrains.
- Our approach also enables **uncertainty estimation** through posterior covariance, which has not been considered in existing RFF-driven residual dynamics literature (e.g., Zhou and Tzoumas, 2025).
- BLR-RFF provides a vehicle motion model and constraints within a **robust model predictive controller (RMPC)** framework capable of updating such a model **online** while performing field tasks. The details and experimental results of our RMPC integrated with BLR-RFF will be reported in a **full-length paper**.
- We demonstrate BLR-RFF on data collected from **unstructured outdoor environments**, marking the first outdoor validation of an RFF-driven residual dynamics approach.

Problem Setup

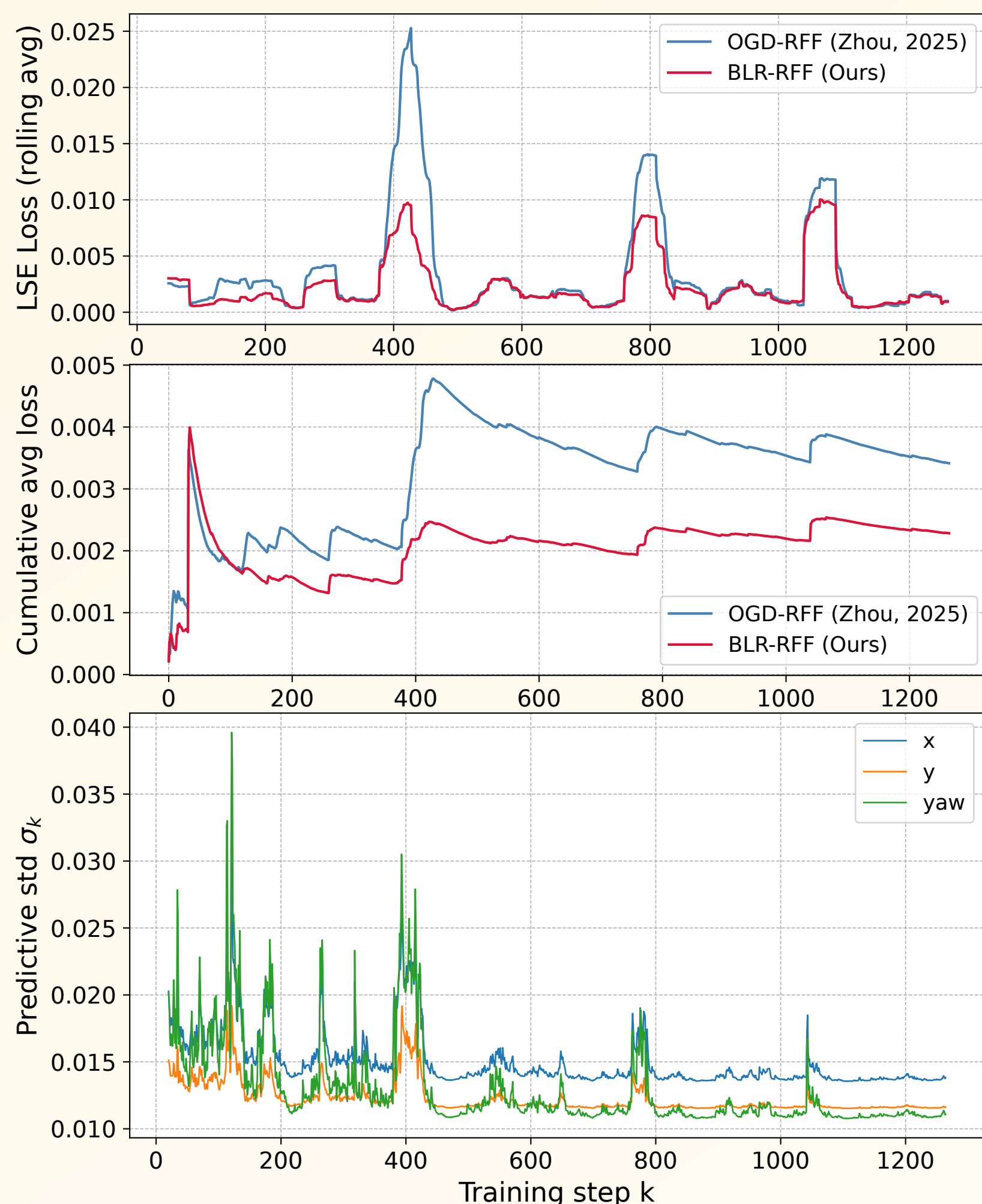


III. Field Experiments: Results

Capability for Model Predictive Control Integration



Capability for Online Deployment



Rolling average LSE loss on uneven ice terrain (short-term learning performance): Our method has **61.4%** (max) lower post-disturbance loss than online gradient descent RFF (OGD-RFF), showing higher robustness.

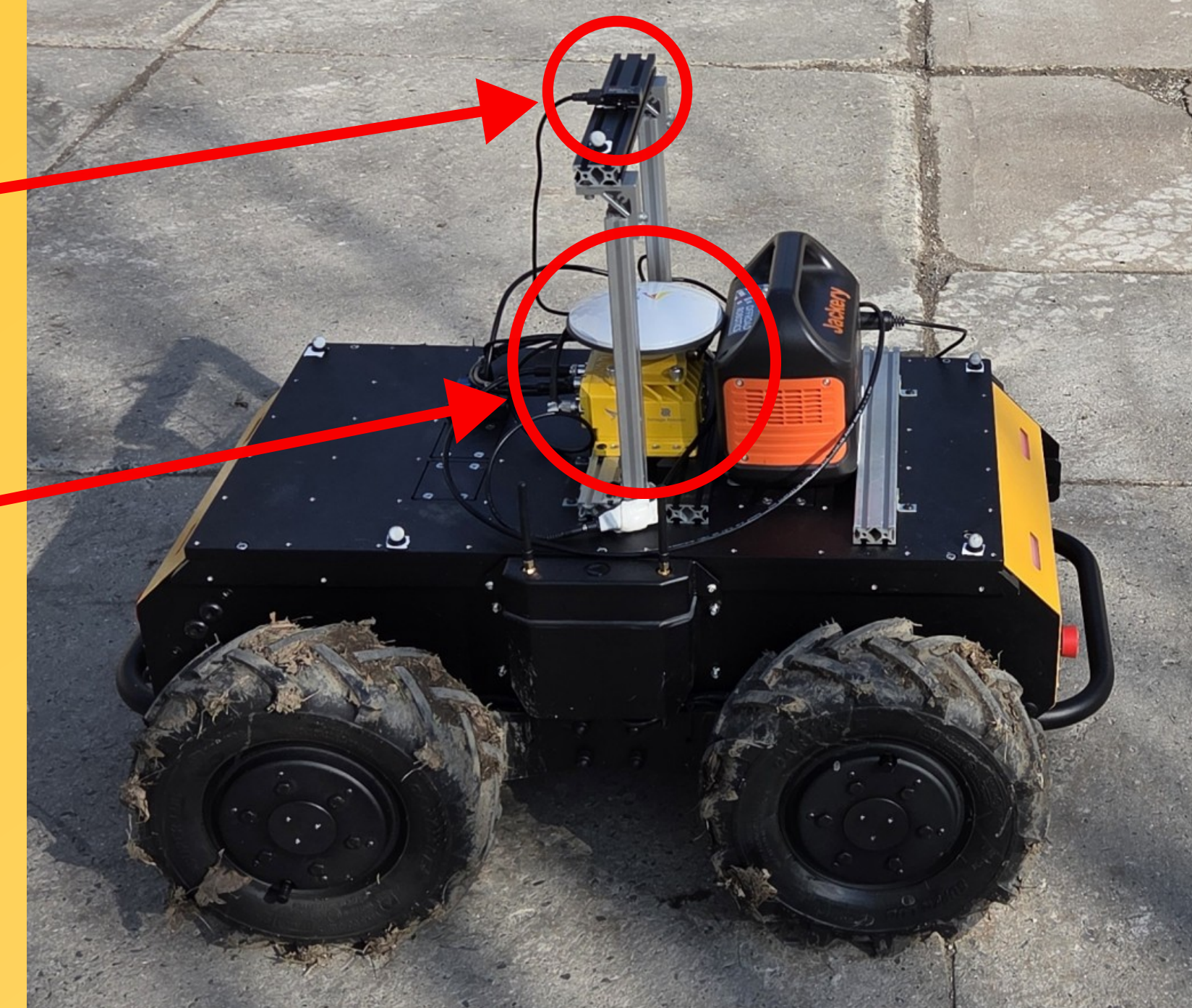
Cumulative average LSE loss on uneven ice terrain (long-term learning trend): Our method converges to a **32.2%** lower cumulative average loss than OGD-RFF.

Predictive standard deviation by BLR-RFF (Uncertainty Awareness): Spikes correspond to the same disturbances seen in the cumulative avg loss plots, where observations temporarily increase uncertainty.

II. Field Experiments: Approach and Setup

Microstrain 3DM-GX5-25 IMU

Duro[®] GPS Receiver with RTK Correction



We set up a *Clearpath Husky A300 UGV Platform* with outdoor localization sensor suite

Experiments were performed on these *three types of terrains*

Concrete - Baseline

BLR-RFF Offline Phase

Identifies prior kernel hyperparameters using Gaussian Process for random Fourier features (RFF) sampling.

BLR-RFF Online Phase

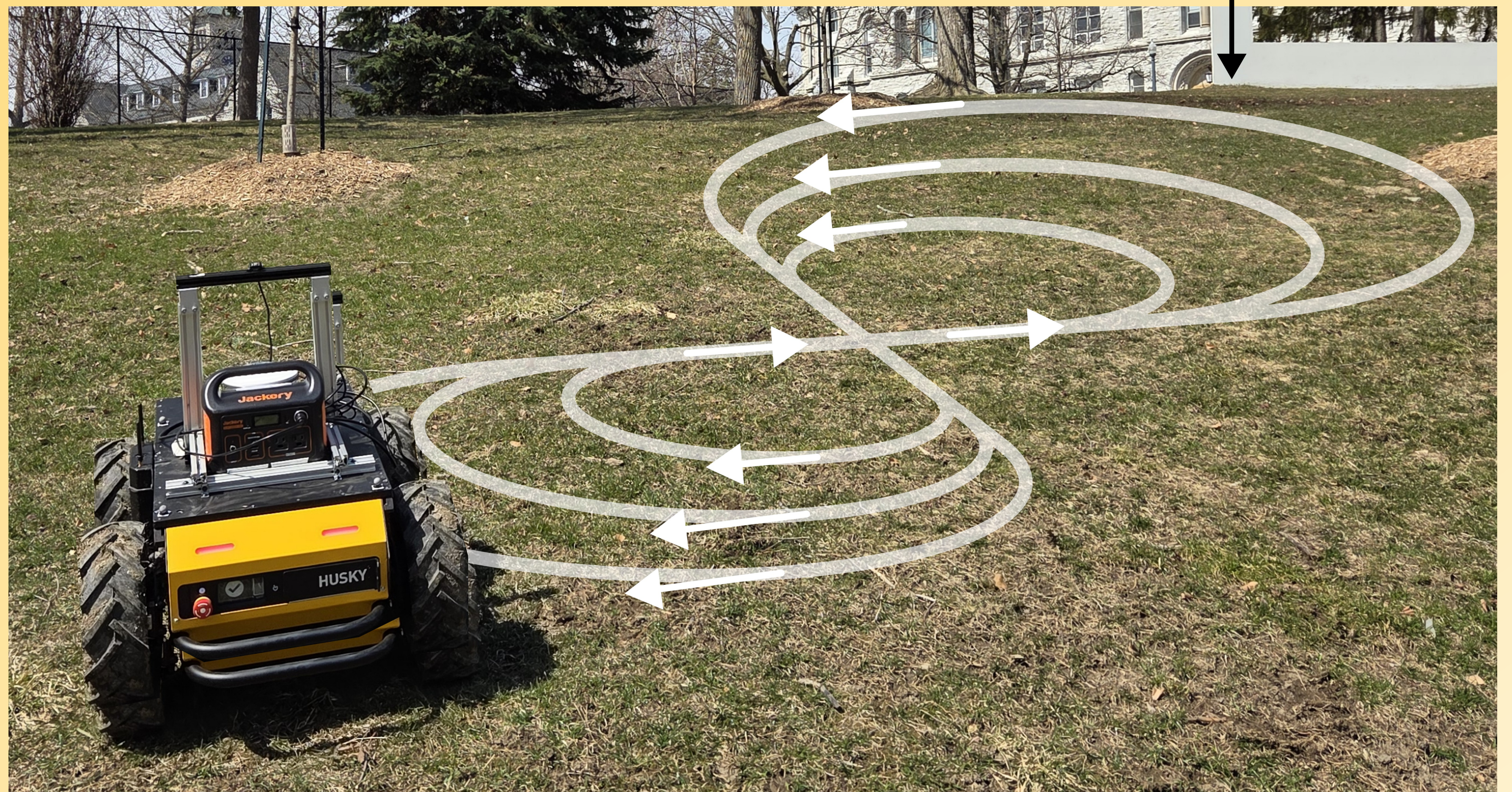
Updates RFF weights (both mean and covariances) using Bayesian linear regression (BLR). The RFFs are sampled to approximate the kernel function from Offline Phase.

Grass - Unseen

Uneven Ice - Unseen

Field Experiment Illustration with Evaluation Path:

Path tracking tasks for all terrains are evaluated on the path shown below using a nominal MPC with unicycle kinematics. The photo is taken during a **supplementary experiment** on a **sloped terrain** where specific improvement of our approach is needed.



References

Zhou, H., and Tzoumas, V. (2025). Simultaneous system identification and model predictive control with no dynamic regret. IEEE Transactions on Robotics, vol. 41, pp. 4322-4341.
Wang, J., Fader, M. T. H., and Marshall, J. A. (2023). Learning-based model predictive control for improved mobile robot path following using Gaussian processes and feedback linearization. Journal of Field Robotics, vol. 40, no. 5, pp. 1014-1033.