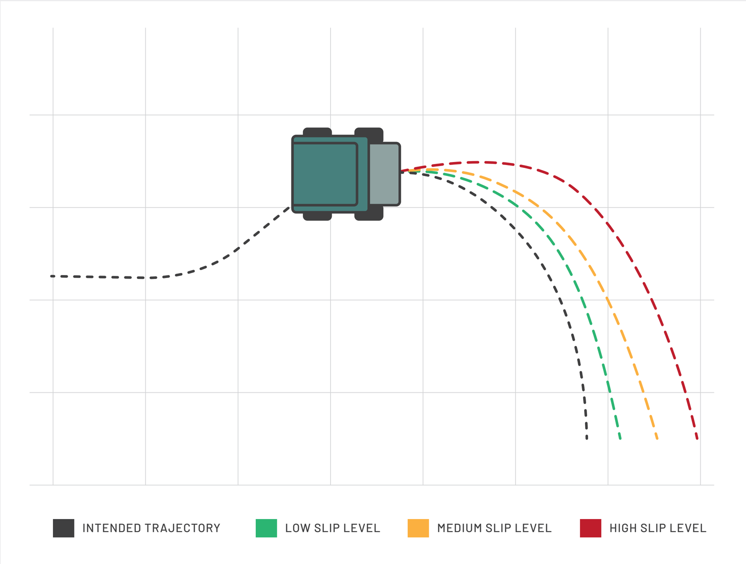
DON'T BE FOOLED BY A SLIP

Enhancing Robot Localization with Machine Learning

FOUR POINT
AUTONOMOUS TRANSPORT PLATFORM

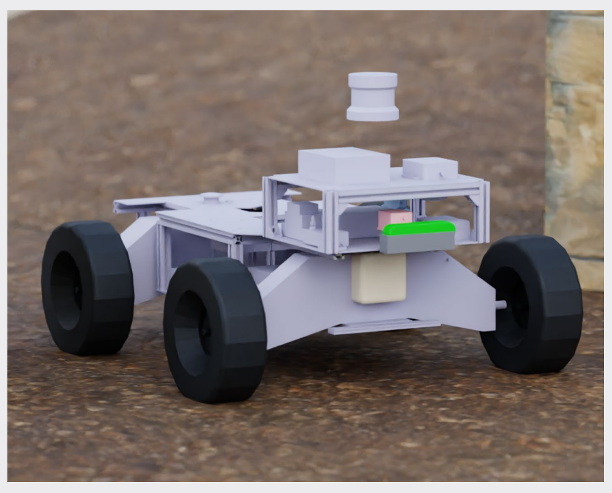


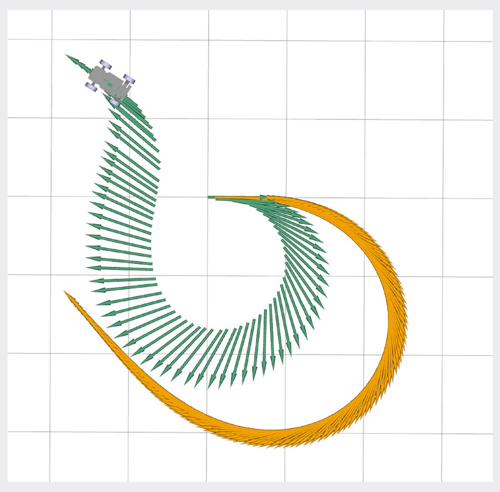
INITIAL ASSUMPTIONS

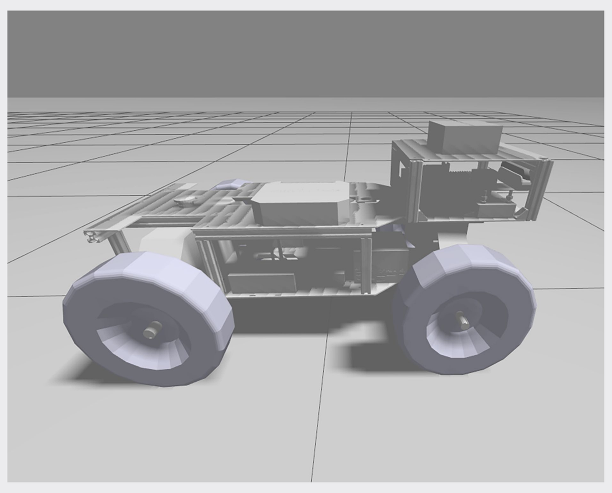
1. We define slip as a condition where the robot loses traction, resulting in an alteration of its path.
2. An IMU provides supplementary data to the wheel odometry, mitigating the influence of anomalies on the combined odometry.
3. Integration of a slippage error without adaptive uncertainty mechanism will break the odometry estimation.

PROJECT OUTLINE

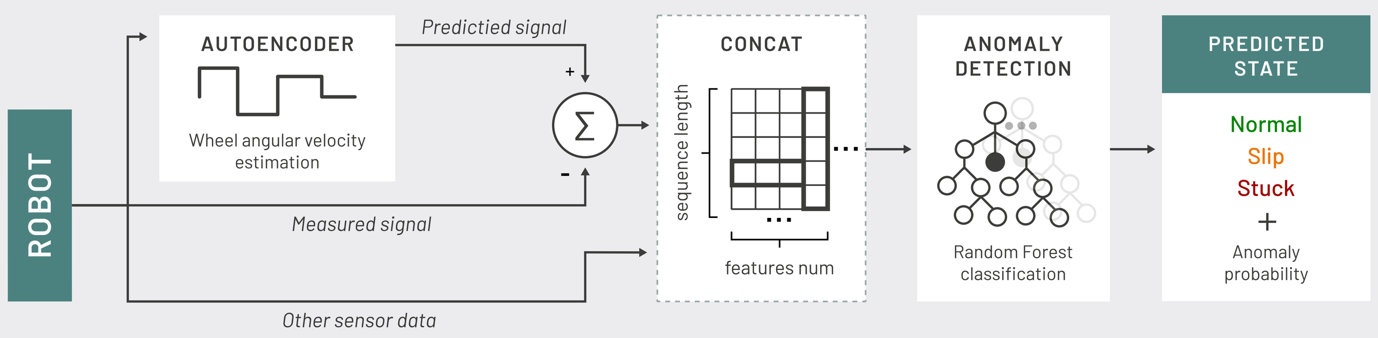
- Creating a synthetic dataset
- Development of slip detection system
- Integration with sensor fusion process
- Testing in the simulator







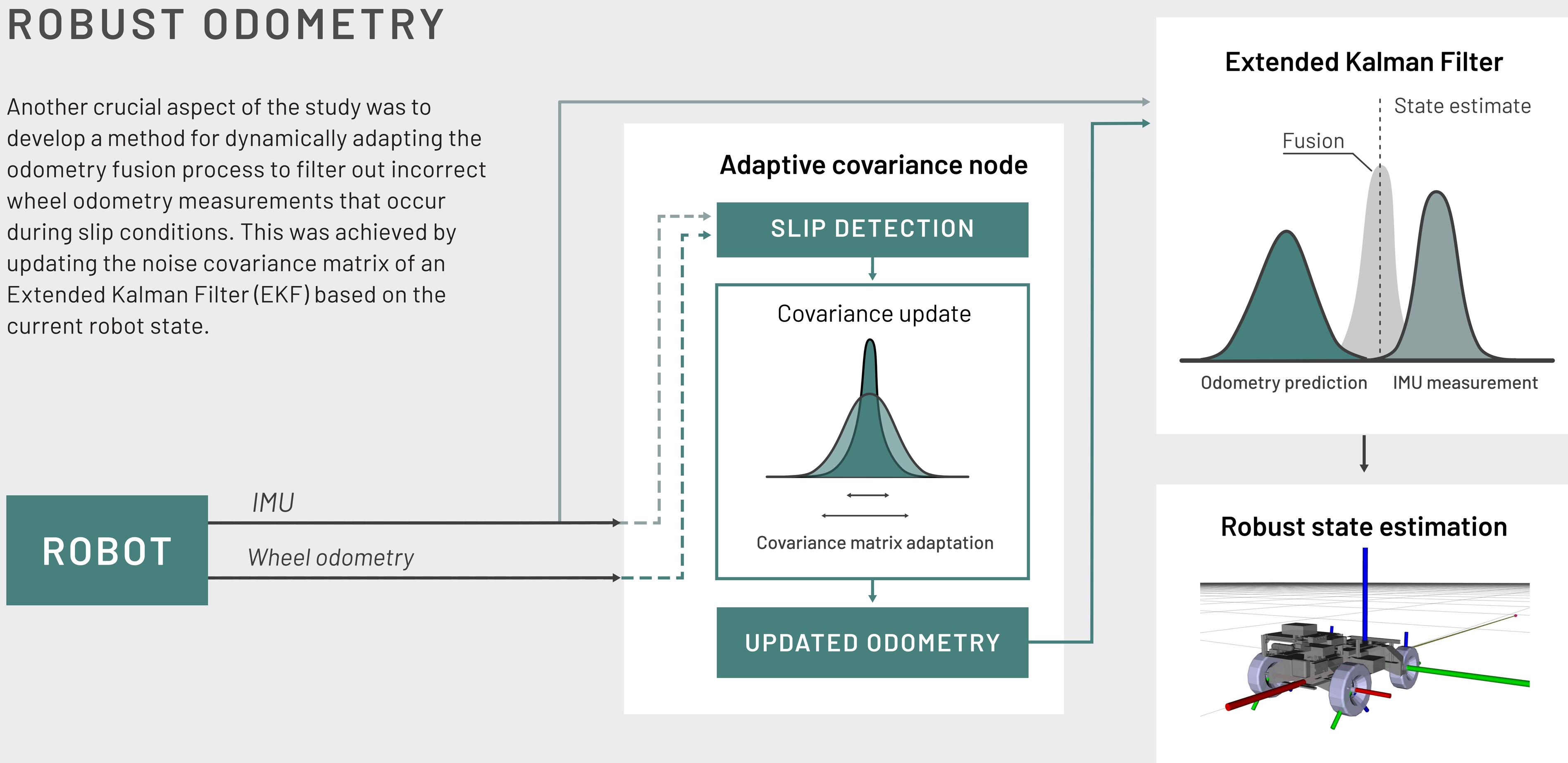
SLIP DETECTION SYSTEM



In our workflow, we have utilized an autoencoder model trained on a dataset of rides without abnormal states occurring. It serves as a state observer, and therefore, we treat an increase in reconstruction error as one of the indicators of a possible anomaly.

ROBUST ODOMETRY

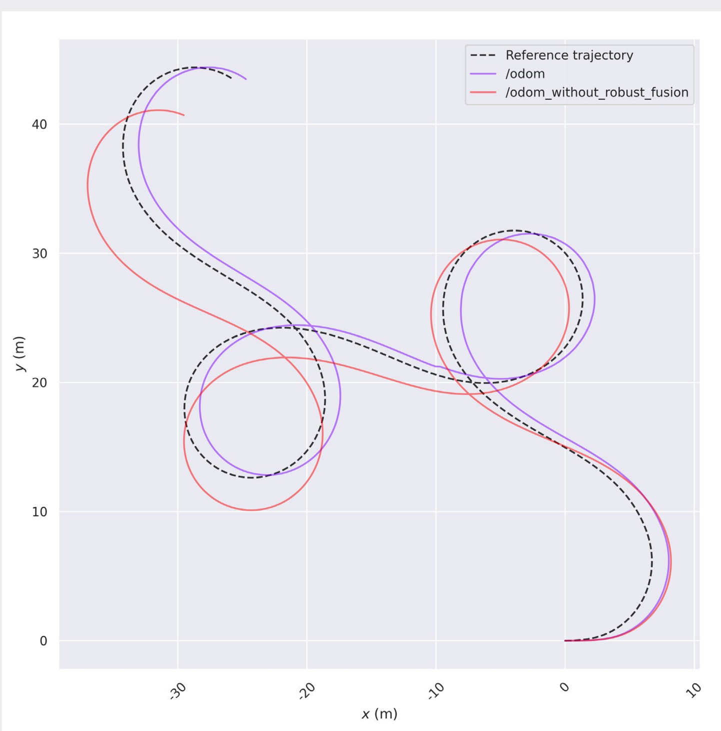
Another crucial aspect of the study was to develop a method for dynamically adapting the odometry fusion process to filter out incorrect wheel odometry measurements that occur during slip conditions. This was achieved by updating the noise covariance matrix of an Extended Kalman Filter (EKF) based on the current robot state.



PROMISING RESULTS

The conducted experiments demonstrated an increase in odometry accuracy in slippery conditions. We observed a reduction in absolute position error by an average of 3.420 cm/m and 0.307 degrees/m compared to traditional fusion. Our next step is to test the robust odometry in real-world scenarios to assess the reality gap and explore its potential applications in robotics.

WITHOUT ROBUST FUSION:	TRAJ 1	TRAJ 2	TRAJ 3	MEAN	STD	
APE tran [cm/m]	2,840	6,560	6,060	5,153	1,542	
APR rot [deg/m]	0,067	0,248	0,620	0,312	0,206	
RPE trans [cm]	1,800	8,040	10,990	6,943	3,429	
RPE rot [deg]	0,471	0,176	0,484	0,377	0,134	
WITH ROBUST FUSION:	**TRAJ 1**	**TRAJ 2**	**TRAJ 3**	**MEAN**	**STD**	**ERROR IMPROVEMENT**
APE tran [cm/m]	0,630	1,050	3,520	1,733	1,191	**-3,420**
APR rot [deg/m]	0,003	0,004	0,006	0,004	0,001	**-0,307**
RPE trans [cm]	1,770	8,030	10,950	6,917	3,431	**-0,027**
RPE rot [deg]	0,074	0,073	0,052	0,066	0,009	**-0,311**
Traj length [m]	**168**	**88**	**68**			
Slipperiness	**low**	**medium**	**high**			



What is the problem?

Commonly used localization systems that rely on fusion IMU and wheel odometry data are highly affected by slippage.

Determining a robot's position and orientation is essential for autonomous systems. Fusing data from proprioceptive sensors such as IMU and wheel odometry is a cost-effective localization solution under ideal, pure rolling conditions. Unfortunately, this assumption does not hold for most real-world use cases. Slip conditions lead to highly inaccurate state estimations from wheel odometry, negatively impacting the entire system's correct operation.

What is our hypothesis?

A machine learning anomaly detection system with sensor fusion will enhance state estimation.

We need the ability to detect anomaly states to achieve greater robustness in IMU and wheel encoder odometry. We can filter out misleading data with a real-time anomaly detection system and the redundant information from the IMU. We can achieve this by integrating our model with the sensor fusion process. This approach will reduce state estimation errors and provide a reliable source of displacement for global localization systems.

What is our approach?

We trained an anomaly detection model and used its outputs to dynamically adjust the sensor fusion process.

Due to the complexity of robot states, wheel-ground interactions, and measurement noises, we used machine-learning methods instead of simple thresholding. We used a simulator to collect the dataset for model training and later validated our approach. With information about the robot's state, we periodically updated the noise covariance matrix of the Extended Kalman Filter, which was responsible for the fusion process.

What are outcomes?

We significantly reduced both relative and absolute pose errors, resulting in a noticeable improvement in robot localization.

We conducted tests in a simulator with different ground friction levels. The developed system could detect anomalous robot states and use that information to reduce state estimation errors. The more slippery the ride surface was, the better the outcome from our robust fusion was compared to the traditional approach. We proved that slip-aware state estimation methods perform better than traditional ones, especially in harsh environments.