Distributed Robot Perception for Tracked Vehicles

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***Abstract*—Accurate estimation and compensation of slippage are critical challenges for tracked robots operating in unstructured terrain. This work presents a novel real-time method for estimating longitudinal and lateral slippage in a tracked vehicle using the Iterative Re-weighted Least Squares (IRLS) algorithm. By combining data from proprio-ceptive and extero-ceptive sensors, the IRLS-based estimator is designed to predict slippages using only wheel speeds, GPS and IMU readings. We validate our approach in a simulated environment, comparing it to two other methods: a baseline with no slippage compensation and a prediction technique based on a exponential function approximation. Our estimation method adapts over time through data-driven updates and enables a slippage-aware controller [1] to achieve better trajectory tracking performance with respect to a fixed parameter estimator.**

I. Introduction

The accurate estimation of slippage represents a significant challenge in robotics, particularly for wheeled robots operating in dynamic environments. The phenomenon of slippage has the potential to significantly impact a robot's ability to navigate autonomously, and perform tasks, thereby making it a pivotal issue in achieving the final objective of a task (e.g. planetary exploration [2]). When a robot moves through terrains with different characteristics, whether it's uneven ground, wet surfaces, or other unpredictable conditions, its motion can be influenced by numerous interaction factors that are often difficult to predict or measure. In such scenarios, accurately estimating slippage is essential for ensuring reliable operation and effective control. Slippage occurs when the robot wheels or tracks lose adhesion to the terrain, causing a discrepancy between the actual vehicle movement and the one predicted by the kinematic model.

Tracked Mobile Robots (TMR) provide a large contact area with the ground, offering enhanced mobility in unstructured environments. However, the skid steering effect, intrinsically present in tracked vehicles, involves the occurrence of both longitudinal and lateral slippage, which poses challenges for precise control and path tracking. To address these challenges, kinematic models must be adapted to account for the effects of slippage.

J.Y. Wong's work [3] provides a comprehensive review of research in the field of vehicle-terrain interaction, commonly known as terramechanics, a subject essential for simulating vehicle behavior on diverse terrains. Building on this, Al-Milli et al. [4] introduced a model to predict the traversability of skid-steered vehicles on soft terrain, addressing excessive slippage during turns. Ahn et al. [5] used an Extended Kalman Filter (EKF) integrated with a soil model to estimate track-soil interactions in real time, identifying critical soil parameters like cohesion and friction angle for enhanced control. Zhao et al. [6] proposed a trajectory prediction method for tracked robots using EKF and an Improved Sliding Mode Observer (ISMO) to estimate slippage, improving navigation on varied terrains. Moosavian and Kalantari [7] experimentally modeled slip in tracked robots, using exponential functions based on path curvature to estimate slip coefficients.

In this work, we propose a novel method for real-time estimation and compensation of both longitudinal and lateral slippage using an Iterative Reweighted Least Squares (IRLS) algorithm [8]. Our approach employs proprioceptive (IMU, encoders) and exteroceptive (GPS) sensors to estimate slippage by comparing the tracks' velocity predicted by a kinematic model with the actual velocity measurements from the encoders. Once sufficient data is recorded, the IRLS-based estimator is continuously fitted to the data. After the parameters are optimized, the estimator can predict slippage using only the wheel speeds as inputs. This method utilizes multiple robots to accelerate data collection and fit the estimator in a distributed manner. We will observe that the a compensation based on the proposed approach effectively reduces the tracking error, showing improvement in convergence over time. The terrain is divided into patches with distinct characteristics, with the exact location of each patch assumed to be known.

A. Problem Formulation

Given a composition of terrains with varying friction coefficients and a closed-loop desired trajectory, our objective is to minimize the tracking error in both position and orientation by performing real-time estimation and compensation of slippage. In this context, we consider a scenario with an arbitrary number of robots (five in our case) randomly positioned along the trajectory as shown in Fig 1.

The objective is to construct a *distributed slippage* map, where each terrain patch is associated with a *estimator* that utilizes the left and right wheel speeds ω_L and ω_R to predict the slippage components: β_L and β_R, representing longitudinal slippage, and α, representing lateral slippage. After the initial lap, during which each robot collects sufficient data, the IRLS algorithm is applied to generate an estimation based on the local data. This estimate is subsequently updated after every half-lap as new data is collected. The robots, connected via point-to-point communication, share their local estimates to collaboratively refine a global estimate. Each local estimator update results in a corresponding update to the global estimator. To validate the approach, we will compare the average

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tracking error across three methods: no slippage compensation, a compensation based on an exponential estimation proposed in [1], and a compensation based on the IRLS-estimation introduced in this work.

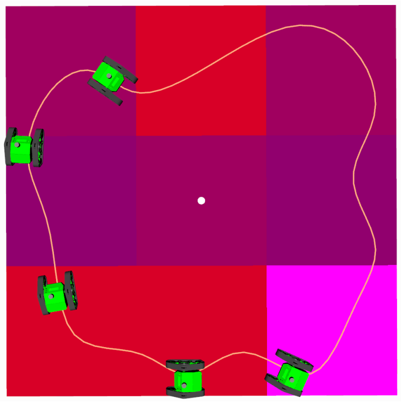

Fig. 1. RVIZ visualization of the tractor simulation, depicting the desired trajectory and the grid map representing terrain patches with distinct friction coefficients.

B. Robot Platform

The robots employed in this experiment comprise five Robodyne MAXXII tracked robots. The MAXXII is a skid-steering unmanned ground vehicle (UGV) designed to ensure optimal traction across a range of terrains, including both soft and hard surfaces. Each robot is equipped with a number of advanced sensors, including a 9-degree-of-freedom (9DOF) inertial measurement unit (IMU), such as the XSens Mti-300, and a U-blox real-time kinematic (RTK) GPS. Additionally, the wheel encoders on the robot's tracks measure the actual velocities of the tracks. This data is instrumental in determining whether the robot is experiencing slippage with respect to the robot base, thereby allowing for the evaluation of traction performance under varying conditions.

As the present study is conducted within a simulated environment, the sensor data is inherently deterministic in nature. To more accurately replicate real-world conditions we added to each sensor a random Gaussian noise.

II. Proposed Solution

A. Lyapunov Based Control of tracked vehicle

To control the tracked robot along the desired trajectory, we utilize a Lyapunov-based controller, developed in [1]. Although the primary focus of this work is on the estimation process, understanding the controller is essential for the role of slippage values in affecting the trajectory tracking. The tracked vehicle's model is an adapted version of the unicycle model, with the following kinematic equations [9]:

$$\begin{aligned} \dot{x} &= \frac{v}{\cos(\alpha)} \cos(\theta + \alpha) \\ \dot{y} &= \frac{v}{\sin(\alpha)} \sin(\theta + \alpha) \\ \dot{\theta} &= \omega \end{aligned} \tag{1}$$

where x and y are the Cartesian coordinates in the world frame, θ is the orientation with respect to the x-axis, v is the forward velocity, ω is the angular velocity, and α represents the lateral slippage angle, which depends on the terrain and robot characteristics. We designed a non-linear control law based on the following Lyapunov function (see [1] for details):

$$V = \frac{1}{2}(e_x^2 + e_y^2) + (1 - \cos(e_\theta + \alpha)) \tag{2}$$

To achieve globally asymptotic convergence, the control inputs are selected as follows:

$$\begin{aligned} v &= (v_d + \delta v)\cos(\alpha) \\ \omega &= \omega_d + \delta\omega \end{aligned} \tag{3}$$

where

$$\begin{aligned} \delta v &= -k_p e_{xy} \cos(\psi - (\theta + \alpha)) \\ \delta\omega &= -v_d e_{xy} \frac{1}{\cos(\frac{\alpha + e_\theta}{2})} \sin\left(\psi - \frac{\alpha + \Delta}{2}\right) \\ &\quad - k_\theta \sin(e_\theta + \alpha) - \dot{\alpha} \end{aligned} \tag{4}$$

where e_{xy} and e_θ are the errors between the actual and desired states. (3) can be mapped to sprocket wheel speed ω_L, ω_R that serve as set-points for the low-level controller. The longitudinal slippages β_L and β_R for the left and right tracks, directly affect sprocket wheels, and can be computed by comparing the actual track velocities, derived from the body-frame tangential velocity $v_{b,x}$ and ω, with encoder-based velocities.

$$\begin{aligned} \beta_L &= v_{enc_L} - v_{track_L} \\ \beta_R &= v_{enc_R} - v_{track_R} \end{aligned} \tag{5}$$

where $v_{enc_{L,R}} = R\omega_{L,R}$ are track velocities estimated from encoder velocities and R is the sprocket radius, while $v_{track_{L,R}}$ are the expected velocities given by:

$$\begin{aligned} v_{trackL} &= v_{b,x} - \frac{\omega B}{2} \\ v_{trackR} &= v_{b,x} + \frac{\omega B}{2} \end{aligned} \tag{6}$$

where B is the track width. The lateral (or side) slippage angle α is calculated using only the body-frame velocity components:

$$\alpha = atan2(v_{b,y}, v_{b,x}) \tag{7}$$

B. Distributed IRLS Slippage estimation

To estimate the slippage values for each robot, we employ an IRLS algorithm. The decision to use IRLS was driven by two key factors:

- **Near-Linearity of Slippage Values**: Through our analysis (see Section III), we found that the slippage values, particularly the longitudinal slippage components β_L and β_R, exhibit near-linear behavior with respect to ω_L and ω_R. The lateral slippage angle α shows more nonlinearity characteristics derived from the $atan2$ function. To handle this problem, we employ a form of polynomial regression to keep the same algorithm for $\beta_{L,R}$ and α.

- **Handling Sensor Uncertainty**: The second motivation for using IRLS is its ability to manage uncertainty, which arises from the fusion of data from multiple sensors such as encoders, GPS, and IMU from each robot in a nontrivial way. These sensors introduce varying levels of noise and potential outliers into the data. IRLS improves robustness by iteratively updating the weights of the least squares regression based on the residuals. This process reduces the impact of noisy or inaccurate data, ensuring more reliable estimates.

The predicted value for the lateral slippage α is directly applied in the control equation (3), influencing both the commanded forward v and angular velocity ω. Next the predicted values of the track longitudinal slippages $\beta_L(\omega_L, \omega_R)$, $\beta_R(\omega_L, \omega_R)$, are employed to correct the set-points ω_L, ω_R:

$$\omega_{L,R}^{des} = \omega_{L,R} + \frac{1}{R}\beta_{L,R} \tag{8}$$

III. Implementation Details

The entire simulation[1] is employing a distributed parameter model of the tracked vehicles which accounts for detailed terra-mechanics interactions and is implemented inside the Locosim robotic framework [10]. A closed trajectory with different radius of curvature is implemented connecting a set of via-points with cubic splines. As previously mentioned, the terrain is defined as a 9×9 meter area, composed of multiple patches 3×3 meters in size (see Fig. 1). Each patch is characterized by a different friction coefficient. The patch size was chosen to ensure that the robot can traverse an entire patch with its full body, while allowing variations in orientation and velocities. This configuration simulates an unstructured terrain where the robot experiences varying slippage conditions that should estimate and compensate for. The default friction coefficient was set to 0.1. We use this value as a baseline and introduce slight random variations (0.09041, 0.13349, 0.15680) to construct the friction coefficient map. Since the locations of the patches are assumed to be known, the estimation problem involves creating a separate estimator for each patch. Each robot has its own slippage map, where each patch corresponds to a specific estimator. As the robot traverses the terrain, the process of local and global estimation is applied to each of these estimators. A terrain map class allows the robot to retrieve the correct patch based on its x, y coordinates, ensuring that the appropriate estimator is selected for each section of the terrain. This same process is also used to manage the parameters of the exponential estimation presented in [1].

A. Analysis of Slippage Linearity and Motivation for IRLS

Figure 2 presents 3D plots of these slippage surfaces in relation to the left and right wheel speeds, ω_L and ω_R. The data was identified in [1] by collecting slippage values during the execution of an open-loop velocity trajectory on terrain with a default friction coefficient $\mu = 0.1$. The Figure

[1]A video of the simulation can be found at this link.

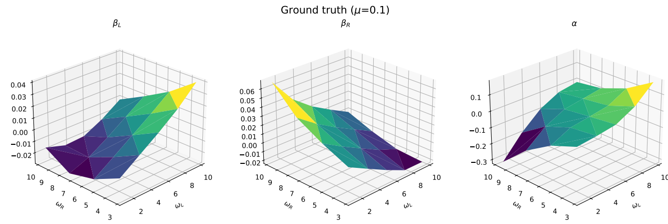

Fig. 2. 3D visualization of the ground truth slippage surfaces for β_L, β_R, and α as functions of the left and right wheel velocities ω_L and ω_R. The frictiction coefficient is set to μ = 0.1

shows that, for a certain range of low, positive velocities, the longitudinal slippage components β_L and β_R exhibit nearly linear behavior. In contrast, the lateral slippage component α presents non-linear characteristics, particularly near the extremes $\{(\omega_{L,\min}, \omega_{R,\max}), (\omega_{L,\max}, \omega_{R,\min})\}$. To manage the moderate non-linearity observed, we opted for a third-order polynomial regression. While polynomial regression models non-linear relationships, it remains a linear statistical estimation problem, allowing us to apply the IRLS algorithm without modifications. This approach effectively balances the complexity of the model with the observed near-linearity of the slippage components.

IV. Results

In this section we compare the ground-truth slippage surfaces obtained in [1] with those produced by our estimation method to evaluate the accuracy and effectiveness of our approach. The primary objective is to assess the accuracy of the slippage estimation and to validate the effectiveness of our approach in comparison to a method which involves a fixed parameter function approximator based on exponentials, particularly in terms of trajectory tracking improvement. We conducted the same simulation with three different slippage compensation strategies: (1) the baseline, where no slippage estimation is applied, assuming the vehicle is controlled as a unicycle (see [1]), (2) our proposed approach, which employs a distributed IRLS algorithm to estimate slippage parameters, and (3) the approach based on the exponential approximation. The estimated parameters in both 2), 3) case are used in the slippage-aware controller (3). In Fig. 3, we see that the exponential approximation method does not change its tracking accuracy over time, as it relies on precomputed constants and does not adapt to new data like while the IRLS approach does. The advantage of the IRLS approach can be showcased looking how the average of the tracking errors evolves as a function of the number of completed laps in Fig. 4 where the IRLS method demonstrates a dramatic improvement over time outperforming both the baseline and the exponential methods.

Fig. 5 contains time series data for the slippage components estimated using the IRLS and the exponential approximation methods. The signal obtained from the ground truth slippage component is notably noisy due to the integration of multiple sensor measurements. An initial observation is that, as previously explained, IRLS does not produce any estimates during the first lap, whereas the exponential approximation begins to

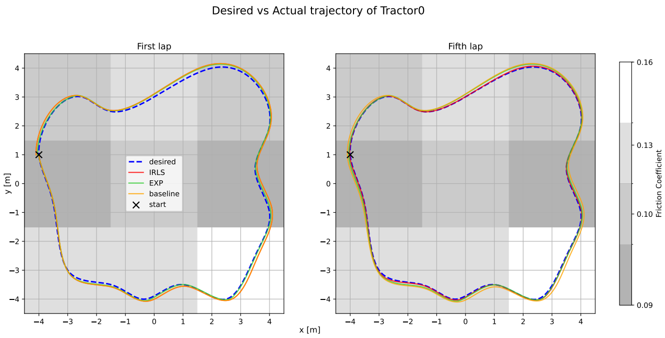

Fig. 3. Comparison of the desired trajectory and the actual trajectory realized during the first and fifth laps using three slippage compensation approaches. The comparison highlights the trajectory tracking performance and improvement over time for each method. In background, the friction map is reported.

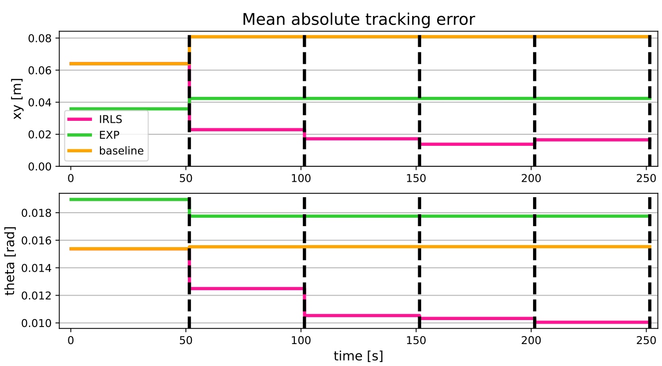

Fig. 4. Average Tracking Error across traveled laps

correct the slippage immediately. It is evident that for the slippage components β_L and β_R, the exponential method tends to overestimate positive values while zeroing out negative values. Conversely, the exponential approach provides a more accurate prediction for the α component. This discrepancy suggests that the exponential approximation may not adequately capture the near-linear characteristics of the slippage components β_L and β_R. Regarding the IRLS estimates, the second lap exhibits some episodes of overestimation, which diminishes in the third lap thanks to the incorporation of new data and improved weighting accuracy.

Finally, to visually compare the surface shapes produced by our IRLS estimator and those computed by [1] for a friction coeff of $\mu = 0.1$, a 3D plot containing the three surfaces is presented in Fig. 6. As observed, the overlay for β_L in the lower range of ω_L is not accurate, showing some discrepancies. Regarding α, we can see, as previously discussed, a lack of generalization at both the upper and lower margins of the value range. Despite this characteristics, overall, the overlay is acceptable, and we consider our IRLS approach to provide a satisfactory approximation compared to the ground truth data. In this work, we assumed an *a-priori* knowledge of the terrain. In future research, we plan to develop a Neural Network (e.g., [11]) capable of identifying the type

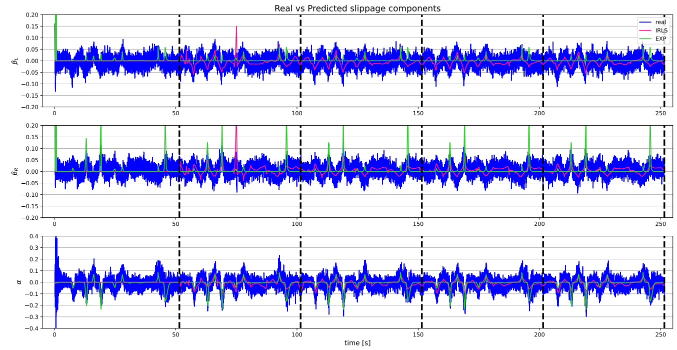

Fig. 5. Time series of calculated and predicted slippage components over laps.

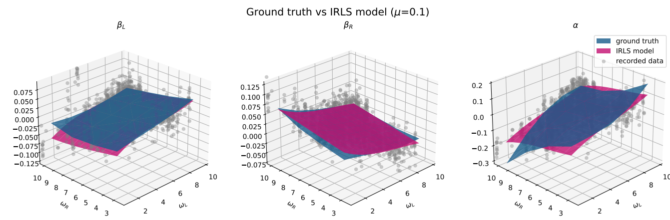

Fig. 6. True vs Predicted plot of the three slippage components obtained with IRLS

of terrain at each robot's location. This information will be used as input for our local estimator, enabling the creation of a *slippage map* of the terrain.

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