Numerical Simulations for Planetary Rovers Safe Navigation and LIDAR Based Localization

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Abstract—Space exploration rovers are designed to investigate the surface of celestial bodies in the Solar System, seeking habitability conditions and biosignatures. These vehicles are equipped with instrumentation and sensors that allow accomplishing in-situ operations. To increase their access capability to harsh environments, onboard systems are included to enable obstacle avoidance and slip prediction that represent fundamental functionalities for safe navigation. This work focuses on the implementation of a method that accurately reproduces the wheel-soil interaction and predicts rovers’ performances in different scenarios (e.g., cloddy/drift terrain type, steep terrains). We implemented a 3D model of a rover to simulate its navigation with obstacles on the path. Our estimated trajectory is obtained through the Light Detection And Ranging (LIDAR) data processing, which enables the simultaneous localization and mapping (SLAM).

Keywords—Navigation, path planning, obstacle avoidance, simultaneous localization and mapping, LIDAR

I. INTRODUCTION

Rover navigation on planetary surfaces is strongly affected by the explored environment. The effect of low–gravity has a significant impact on the wheel-soil interaction, causing a reduction in traction [1]. High slippery terrains, slopes and obstacles could endanger the mission, limiting the rover locomotion [2]. The NASA’s rover Spirit, for example, got stuck in soft soil, descloping the mission to a stationary science platform [3]. To cope with these hazards, rovers host onboard subsystems devoted to obstacle avoidance and slip prediction [4]. Soil Properties and Object Classification (SPOC) is a software built upon a deep Convolutional Neural Network (CNN) that labels various terrain types analyzing Curiosity’s NavCam images and improves the mission path planning [5]. These capabilities expand rovers’ autonomy to enhance the number of sites they can visit and the experiments they can conduct. Predictions on the rover performances are usually based on empirical approaches (i.e., the model is built by learning a nonlinear approximation function that maps terrain slopes to the measured slip through a standard nonlinear regression technique [5]). A drawback of this method is that data must be collected through many experiments on Earth (data from past rover missions are not useful, mainly due to differences in size and mass of the rovers) [5,6]. An alternative approach is based on identifying soil parameters [7]. A better modeling of the terrain allows us to accurately define the dynamical equations [8]. By assuming a rigid wheel on soft soil to represent the wheel–soil interaction [9], previous studies (e.g., [10]) carried out simulations of the traverses of the NASA’s Mars Exploration Rovers (MER) Spirit and Opportunity. An independent approach was proposed by Gibbesch & Schäfer [11] through the integration of the Multibody System simulation to investigate the dynamic of vehicle, including the suspension. This work is also based on the rigid wheel assumption, which is not adequate to simulate the trajectory of rovers equipped with flexible wheels, e.g., ESA’s ExoMars rover [12].

Our numerical simulations were carried out with an accurate modeling of the compliance of both wheel and ground [13-14]. A 3D model of the rover was developed by using size and mass of the ESA’s rover ExoMars [15] (Fig. 1). Different terrain types and slopes were also accounted for to investigate the discrepancies in the evolution of the rover trajectory.

To enable an accurate estimation of the rover position across different environments that include hazards, we implemented a simultaneous localization and mapping (SLAM) system with a Light Detection And Ranging (LIDAR) instrument. The SLAM algorithm provides precise localization of the rover and identification of the hazards along the path [16]. The LIDAR range data are well-suited to measure the relative distance between the vehicle and the obstacles [17, 18], yielding higher accuracies compared to Wheel Odometry (WO).

II. SPACE ROVER NAVIGATION MODELING

A. Dynamical Model

We modeled the rover’s dynamical equations by assuming compliant wheels on compliant ground. The resistance to the motion acting on the wheels is due to energy

Fig. 1. 3D model of the rover with operative LIDAR sensor in the Gazebo Simulator.
dissipation in both wheel and ground. This hypothesis is suitable to represent motion on unprepared ground, as planetary surfaces. The wheel-soil interaction results in a vertical force \( F_z \), a longitudinal force \( F_x \), a lateral force \( F_y \), and an aligning moment \( M_z \) acting on each vehicle’s wheel [13, 14, 19]. We modeled these forces as follows:

\[
F_z = R_w b \int_{\theta_1}^{\theta_2} [\sigma_z(\theta) \cos(\theta) + \tau_x(\theta) \sin(\theta)] d\theta + 2b \mu \sigma \cos(i)
\]

where \( R_w \) and \( b \) are the radius and the width of the rover’s wheel, respectively; \( n_w \) is the number of the vehicle’s wheels; \( \sigma_z \) is the normal load, and \( \tau_x \) and \( \tau_y \) are the longitudinal and lateral shear stresses, respectively; \( x_g \) is the x-coordinate where the pressure exerted on the ground exceeds the pressure \( p_{gr} \) needed to deform the tire (that stands for an equivalent stiffness of flexible wheels); \( m \) is the vehicle’s mass, \( g \) is the gravitational acceleration of the planet and \( i \) is the slope angle. \( F_\text{by} \) is the bulldozing force per unit width and \( h \) is the sinkage of the wheel; \( \theta_0 \) and \( \theta_1 \) are the angles that identify the portion of the wheel involved in the contact with the ground and must be computed at each step, solving Eq. (1).

The longitudinal slip \( \sigma \) is a key measurement that constrains the traverse in highly-unstructured and natural terrains. This parameter measures the difference between the commanded speed of the vehicle \( \Omega R_w \) (controlled through the wheels angular speed) and its actual speed \( V \):

\[
\sigma = \begin{cases} \frac{\Omega R_w - V}{\Omega R_w} & \text{in driving} \\ \frac{\Omega R_w - V}{V} & \text{in braking} \end{cases}
\]

Once all the interaction forces have been introduced, the method integrates the full set of equations of motion reported in the Model for High Speed Cornering [19, 20]. The vehicle’s trajectory and the evolution of the velocity components, angular speed and acceleration are obtained straightforwardly.

### TABLE I. ROVER PARAMETERS: L IS THE WHEEL BASE AND T IS THE DISTANCE BETWEEN THE KINGPIN AXES OF THE WHEELS. \( v_{\text{max}} \) AND \( v_c \) REPRESENT THE ROVER’S MAXIMUM AND NOMINAL SPEED, RESPECTIVELY.

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Value</th>
<th>( p_{gr} ) [kPa]</th>
<th>( R_w ) [m]</th>
<th>( b ) [m]</th>
<th>( L ) [m]</th>
<th>( t ) [m]</th>
<th>( v_{\text{max}} ) [m/s]</th>
<th>( v_c ) [m/s]</th>
</tr>
</thead>
<tbody>
<tr>
<td>Parameter</td>
<td>310</td>
<td>14.6</td>
<td>0.1425</td>
<td>0.12</td>
<td>1.35</td>
<td>1.2</td>
<td>100</td>
<td>40</td>
</tr>
</tbody>
</table>

### TABLE II. TERRAIN PARAMETERS

<table>
<thead>
<tr>
<th>Soil Properties</th>
<th>Cloddy</th>
<th>Mixed Drift-Cloddy</th>
<th>Drift</th>
</tr>
</thead>
<tbody>
<tr>
<td>( e ) [Pa]</td>
<td>170</td>
<td>220</td>
<td>530</td>
</tr>
<tr>
<td>( \Phi ) [deg]</td>
<td>37.0</td>
<td>33.1</td>
<td>26.4</td>
</tr>
<tr>
<td>( n ) [-]</td>
<td>1</td>
<td>1</td>
<td>1</td>
</tr>
<tr>
<td>( k_c ) [N/m(^{n+1})]</td>
<td>1400</td>
<td>1400</td>
<td>1400</td>
</tr>
<tr>
<td>( k_g ) [N/m(^{n+2})]</td>
<td>820000</td>
<td>820000</td>
<td>820000</td>
</tr>
<tr>
<td>( K_x ), ( K_y ) [m]</td>
<td>0.016</td>
<td>0.016</td>
<td>0.016</td>
</tr>
<tr>
<td>( \rho ) [kg/m(^3)]</td>
<td>1550</td>
<td>1350</td>
<td>1150</td>
</tr>
</tbody>
</table>

B. Traversability of Demanding Terrains

We present here the results of numerical simulations that account for extremely steep terrains (i.e., \( 21^\circ \) and \( 26^\circ \) slopes) with different properties (i.e., cloddy, mixed drift-cloddy and drift). These mission scenarios are consistent with ExoMars extreme operation conditions [15]. Table 1 reports physical and geometrical properties of the modeled rover [15]. Table 2 reports the parameters that define a terrain type, including cohesion \( c \), internal friction angle \( \Phi \), soil cohesive and frictional moduli \( k_c \) and \( k_\Phi \), exponent of sinkage \( n \), moduli of the shear deformation in \( x \) and \( y \) direction \( K_x \) and \( K_y \) and density \( \rho \) [21, 22]. The properties of the soil directly affect the values of normal load \( \sigma_z \) and longitudinal and lateral shear stresses \( \tau_x \) and \( \tau_y \), determining the contact dynamics. The effects of the different terrains types are included in the dynamical model, impacting on the rover’s performances. Each simulation case is based on the assumption of homogeneous and constant soil properties.

A Proportional Derivative (PD) control of the commanded speed was implemented to enable uphill and downhill motion, preventing from the locking condition and higher actual speed than \( v_{\text{max}} \). The control was designed to maintain the actual speed of the vehicle as close as possible to the nominal speed \( v_c \). We assume a constant steering angle of the wheels (\( \delta=4^\circ \)) and initial speed \( V_0=38 \text{ m/h} \).

Fig. 2 (a) and Fig. 2 (c) show the trajectories of the rover with different terrain properties. When the rover traverses a \( 21^\circ \) slope with cloddy soil, it turns around reaching the initial orientation. A mixed drift-cloddy soil leads to a different path that diverges from a closed loop. The steering angle adopted in this simulation is not sufficient to deviate the rover’s path from a straight line in case of a drift terrain. Different trajectory configurations were also obtained with a steeper terrain with \( 26^\circ \) slope for both mixed drift-cloddy and cloddy soil. Fig. 2 (b) shows that the longitudinal slip for a \( 21^\circ \) slope reaches the maximum value in the case of drift soil (\( \sigma=0.71 \)), which suggests the harsh conditions due to this terrain. Fig. 2 (d) reports the longitudinal slip for the \( 26^\circ \) slope traverse, indicating similar slippage for a mixed drift-cloddy soil (\( \sigma=0.70 \)) compared to a drift soil with \( 21^\circ \).
Our results demonstrate the trafficability limits across terrains with different properties [23]. Higher slopes would yield slip ratios close to 1. Therefore, slopes ≤26° and ≤21° are the thresholds for mixed drift-cloddy soil and for drift soil, respectively. These results are in full agreement with previous works (e.g., [15]).

III. SIMULATED TRAJECTORY AND MEASUREMENTS

An accurate modeling of the surface properties and its interaction with the rover’s wheels allow us to simulate the traverse of wheeled vehicles across a Martian-like environment. A thorough definition of the dynamical model is fundamental to determine the evolution of the rover’s trajectory from a starting point to a target, and to simulate the measurements of the instruments that are used to reconstruct the path. A precise knowledge of the rover’s position across the environment is a key factor for safe navigation.

The mission scenario was conceived by accounting for a coarse soil (cloddy) with several hazards, such as rocks, randomly distributed across the site. The local reference frame (X, Y) is supposed to be centered in the initial position of the rover. The X axis points eastwards and the Y axis northwards. The rover path was planned to reach a specific target located at \((X_f, Y_f) = (100.0, 350.0)\) m in the local reference frame. The rover’s initial speed was \(v(t_0) = 38\) m/h = 1.056 \(\cdot\) 10^{-2} m/s. To achieve this objective by avoiding the obstacles, whose coordinates, in this phase, are supposed to be perfectly known, we implemented the following control strategy. We adopted a sequence of steering techniques that allows the rover to follow a fixed direction and to move with constant steering angle. When the distance between the rover and the target is less than 20 m, a proportional control is used for the steering angle and reducing the commanded speed \(v_c\).

Once the path was obtained, the resulting trajectory was simulated by computing and integrating Eqs. (1-4) to account for the interaction forces acting on each wheel [19]. The state of the rover was updated at each time step. During the traverse, we simulated the LIDAR range measurements that were used as input in our trajectory estimator.

Fig. 3 shows the simulated trajectory. The rover is able to reach the final position \((X_f, Y_f) = (100.152, 349.831)\) m with a limited approaching velocity, \(v(t_f) = 1.340 \cdot 10^{-4}\) m/s. The selected path represents a safe option, whereas the shortest trajectory reported in magenta is discarded because of the presence of hazards.
from the instrument field of view (FOV) and to determine the relative distance between landmarks within a 60°, the availability of these observables relies on the presence of landmarks within the LIDAR range and bearing angle measurements associated with the WO and IMU errors are modeled as a zero mean multivariate Gaussian noise ($\sigma_d$=3 cm and $\sigma_p$=0.8°). The initial covariance matrix $P_0$ is a diagonal matrix with $\sigma_q^2$=5 m and $\sigma_v^2$=0.001°, $V$ is the variance matrix and $F_q$ and $F_p$ are the matrices of the partial derivatives of Eq. (6) with respect to $q$ and $v$, evaluated considering zero noise [24]. By applying WO and IMU only, the estimated trajectory would diverge from the reference path (Fig. 5) because of systematic errors that accumulate over time. A further source of error is that WO does not include any information on the wheel slippage. The instability in the reconstructed trajectory is shown with the uncertainty ellipses of the rover’s state (Fig. 5), whose size increases over time, leading to a poor knowledge of the rover’s position in proximity of the target. A more accurate estimation of the rover’s trajectory is then based on the processing of the LIDAR range measurements. These data are acquired onboard the rover with a 60-s sampling rate. The availability of these observables relies on the presence of landmarks within the instrument field of view (FOV) and their relative distance from the rover that should be lower than the LIDAR maximum range (80 m). A new observable is processed to improve the estimation of the rover’s position and to identify the landmark location. The first time a landmark $j$ is detected, its coordinates are included in the state vector $\bar{q}$ = $(x_j, y_j, \psi_j, r_j, \beta_j, ..., x_j, y_j)$ [25]. These additional variables are computed according to:

$$g(q, z_j) = (x_j, y_j)^T = \left(x+r_j\cos(\psi+\beta_j), y+r_j\sin(\psi+\beta_j)\right)$$

where $z_j = (r_j, \beta_j)$ is the observed observable, i.e., the LIDAR range and bearing angle measurements associated with the j-th landmark; $z$ is affected by the noise $w$ associated with the lidar sensor. The noise has a zero mean Gaussian distribution with $\sigma_x=2$ cm and $\sigma_y=0.3°$. The covariance matrix is now defined as follows:

$$P_{k+1} = Y \left(\bar{P}_{k+1} \ 0\right) \gamma^T$$

$W$ is the covariance matrix of the LIDAR sensor noise and $Y$ is the insertion Jacobian:

$$Y = \frac{\partial g}{\partial z} = \begin{pmatrix} I_{n \times n} & 0_{n \times 2} \\ G_x & G_z \end{pmatrix}$$

$G_x = \left(\frac{\partial \beta}{\partial \alpha}, 0_{2 \times n-3}\right)$ and $G_z = \frac{\partial \gamma}{\partial z}$. The matrix size $n$ is the length of the state vector $q$ prior to the identification of the new landmark.

If the same landmark is observed afterwards, the state and the covariance matrix are updated through an Extended Kalman Filter (EKF) algorithm:

$$\tilde{q}_{k+1} = \tilde{q}_{k+1} + K_{k+1}[z_{k+1} - h(\tilde{q}_{k+1})]$$

$$\tilde{P}_{k+1} = [I - K_{k+1}H_{k+1}]\tilde{P}_{k+1}$$
\( h \) is the computed observable and \( K \) is the Kalman gain, computed at each step:

\[
K_{k+1} = P_{k+1}^T H_{k+1}^T S^{-1}
\]

where \( S = H_{k+1} P_{k+1} H_{k+1}^T + H_{w} W H_{w}^T \); \( H \) is the matrix of the partial derivatives of the observed observables with respect to \( q \); \( H_{w} \) is the derivative of the observed observables with respect to \( w \). The non-zero terms of \( H \) are associated with the vehicle’s state and the \( j \)-th landmark coordinates. If the LIDAR detects a group of landmarks the system randomly selects one of them to update the state vector and the covariance matrix.

The additional information provided by the LIDAR significantly improves the performances of the localization system. Fig. 6 highlights that the reconstructed trajectory slightly diverges from the simulated path because of WO errors. The accumulated integration errors also affect significantly the estimate of the landmarks locations, leading to larger discrepancies as the distance from the starting position increases. Fig. 7 (a) shows that the errors in the rover’s position estimates obtained through the SLAM method are almost one order of magnitude lower than those associated with WO only at the end of the path. Furthermore, the SLAM method allows reducing the uncertainty on the estimated position (Fig. 7 (b)).

The SLAM technique mitigates the drift errors of position and heading angle that accumulate over time in WO. A drawback of this method is that the SLAM performances are deeply affected by featureless environments that compromise the accuracy of localization and map updating [26].

V. SUMMARY

Accurate models of the rover’s dynamics were implemented to carry out realistic simulations of rover’s operations in different environments. Since soil properties deeply affect rover navigation, our results account for wheel-soil interaction forces.

By analyzing different terrain conditions and types, we reproduced mission scenarios that are in agreement with the ExoMars expected performances [15]. An accurate modeling of the dynamical equations allowed us to simulate the navigation of a rover across a site with obstacles. By implementing WO and LIDAR instruments, we processed the simulated data to investigate the benefits of simultaneous localization and mapping. Our results are consistent with the expectation, supporting that the adopted technique is well-suited for safe navigation of rovers across rough terrains.

ACKNOWLEDGMENTS

The software developed to carry out the presented simulations is based on Gazebo simulator libraries [27] (http://gazebosim.org).

REFERENCES


