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DIGITAL TWIN AND PHYSICS INFORMED MACHINE LEARNING FOR ROVER MOTION SIMULATION

Abstract

Predicting the motion of rovers on regolith is key for unmanned extraterrestrial exploration to ensure their safety while traversing new terrains and for the successful completion of scientific tasks on Lunar surface. Some terramechanics studies tackle this problem looking at the interactions between wheels and deformable soil made of regolith. Although those techniques provide very accurate results, the computation loads are too heavy to be used in the rovers' real-time decision-making process.

This study aims to reduce the running time of the simulation model while keeping very accurate predictions. To this purpose, Physics Informed Machine Learning (PIML) was identified as a promising architecture as it can capture physical knowledge using ordinary differential equations (ODE) and improve the final solution using data driven machine learning (ML). Additionally, this technique requires significantly less training data which is very useful in the context of space exploration.

The architecture proposed in this paper is composed of two components. The first component consists of an ODE to simulate the physical behavior of the rover. Although not accurate, the ODE predicts the position of the rover simplifying the problem to a rigid body on a rigid slope with a constant friction coefficient. Applying the net forces, this yields to a rough estimation of the positions using analytically solvable ODEs. A neural network is then added as a second component which is trained to compensate the differences between the solutions of the simplified ODE and the ground truth data given by an accurate, but slow, terramechanics simulation engine.

By combining the ODE with a neural network, we demonstrate that the PIML can reduce an error of 60m (ODEs only) to 20cm while drastically reducing the running time. The outputs of the PIML are indeed generated in 400ms where it takes more than 90min with traditional methods to produce the ground truth data with which those outputs are compared.

This research represents a significant advancement in robotic modeling, simulation and prediction methodologies, offering a robust framework that combines foundational physics principles with data-driven machine learning for optimized digital twin techniques. By bridging the gap between accuracy and efficiency, this approach holds great promise for optimizing robotic operations in lunar extraterrestrial environments and autonomous decision making.