INDUSTRIAL TRAINING REPORT

by

Fahad P. P.
19NA30013

A report submitted in partial fulfillment for the award of the degree of
Master of Technology in Ocean Engineering & Naval Architecture

Semester Nine (Autumn) Session 2023-2024

Department of Ocean Engineering and Naval Architecture
Indian Institute of Technology, Kharagpur
Kharagpur, West Bengal, India
Autumn 2023

Contents

Confidentiality Disclaimer

This email and any files transmitted with it are confidential and intended solely for the use of the individual or entity to whom they are addressed. If you have received this email in error please notify the system manager. This message contains confidential information and is intended only for the individual named. If you are not the named addressee you should not disseminate, distribute or copy this e-mail. Please notify the sender immediately by e-mail if you have received this e-mail by mistake and delete this e-mail from your system. If you are not the intended recipient you are notified that disclosing, copying, distributing or taking any action in reliance on the contents of this information is strictly prohibited.

The information provided in this communication pertains to an ongoing project that has not yet been published or publicly disclosed. This content is intended solely for the recipient(s) listed in this communication and is to be treated as strictly confidential.

By accessing or reviewing the materials shared in this communication, you agree to maintain the utmost confidentiality regarding the details, findings, and any related information concerning this project. You are expressly prohibited from sharing, distributing, reproducing, or disclosing any part of this information to any third party, without the explicit written consent of the project stakeholders.

Your commitment to maintaining the confidentiality of this information is paramount. Any unauthorized disclosure or breach of confidentiality may result in legal action and irreparable harm to the ongoing project and its contributors.

We kindly request that you uphold the principles of confidentiality and respect the sensitive nature of this ongoing work. Your cooperation and compliance are greatly appreciated.

Thank you for your understanding and commitment to maintaining the confidentiality of this project.

Sincerely,
Fahad P P
MITACS GRI Fellow 2023
fahad.pp@iitkgp.ac.in

Introduction

System-Level Model Development Engineering Lab

Our mission is to deliver value to our industry partners by helping them make difficult technical decisions with their complex systems. We achieve this through the application of contemporary multi-physics modelling and simulation tools, techniques, and technologies; incorporating concepts from numerous technical fields in order to push boundaries.
The strategic foundation of Sys-MoDEL focuses on solving difficult industry centric, real-world problems by applying a first principles physics-based foundational approach to systematically, yet practically, develop computational models for complex systems. These models are used to execute simulations and extract important insights for developing advanced engineering prototypes. Our research partnerships include: Potential Motors™, NB Power™, Pacific Regional Institute for Marine Energy Development (PRIMED™), Sandia National Labs™, and Maplesoft™.

Research Areas

Vehicle Dynamics Industrial research
Design of advanced controllers and control strategies for semi-autonomous 4-wheel independently driven electric vehicles.

Energy Systems
Probabilistic Reliability Assessment of Transmission Systems using Julia Programming Language.

Wave Energy
Design of advanced controllers and control strategies.

Abstract

This technical report delves into an in-depth exploration of vehicle dynamics, tire-terrain interaction, Smoothed Particle Hydrodynamics (SPH) frameworks, and cutting-edge Deep Learning models. The study involves the modeling of a Newtonian rigid tire geometry within the Chrono Fluid Structure Interaction (FSI) module. A comprehensive parametric study of tire-terrain interaction is conducted, encompassing a wide range of terrain material properties. Moreover, a novel Physics-informed Neural Network (PiNN) model is developed for terrain forecasting using data from the Chrono FSI simulations. The performance of the PiNN model is compared against conventional methods, including Multi-Layer Perceptron (MLP), stacked Long Short-Term Memory (LSTM), and stacked Gated Recurrent Unit (GRU) models. The results showcase the PiNN model's exceptional accuracy in estimating terrain parameters, its minimal computational cost, and its robustness in handling noisy and incomplete data.

Project Background and Objective

In the realm of off-road and space exploration robotics, the interaction between a vehicle's tires and the terrain it traverses plays a pivotal role in determining its performance and safety. The success of rovers in such environments hinges on their ability to effectively navigate, traverse, and adapt to various terrains. Accurate estimation of terrain parameters, such as surface roughness and stiffness, is essential for enhancing the navigation and control strategies of vehicles operating in challenging environments. The central focus of the project involves deriving accurate estimates of terrain parameters through the analysis of tire-terrain interaction data. This information is crucial for enabling rovers to adapt their locomotion strategies based on the encountered terrain, ensuring optimal traction and reduced energy consumption.

The project focus to have a rigorous comparative study of various predictive models for terrain estimation. The models considered include conventional Multi-Layer Perceptron (MLP), stacked Long Short-Term Memory (LSTM), stacked Gated Recurrent Unit (GRU), and a novel Physics-informed Neural Network (PiNN) model. These models have to be trained and evaluated using data obtained from Chrono Fluid Structure Interaction (FSI) simulations. Through the comprehensive model comparison, the project aims to establish the most effective model for terrain parameter estimation.

The project's outcomes have direct implications for the fields of robotics and space exploration. Accurate terrain parameter estimation not only enhances the operational capabilities of off-road vehicles but also contributes to the advancement of space rovers by enabling them to navigate diverse extraterrestrial landscapes with improved precision and efficiency. The project seeks to bridge the gap between tire-terrain interaction data and accurate terrain parameter estimation for off-road and space exploration rovers. By leveraging advanced machine learning techniques and a thorough model comparison, the project aims to contribute to the development of vehicles capable of efficiently navigating complex and challenging terrains.

Methodology

The following methods are employed to comprehensively address the objectives of the project:

Literature Review and Conceptual Framework:

The initial phase involves an in-depth literature review to gain a profound understanding of vehicle dynamics, tire-terrain interaction, state-of-the-art SPH frameworks, and leading-edge Deep Learning models. This foundational knowledge serves as the conceptual framework for the subsequent methodologies.

Case Modeling in Chrono FSI module:

Within the Chrono Fluid Structure Interaction framework, the project involves modeling a Newtonian rigid tire geometry to simulate the intricate interactions between the tire and the varying terrain conditions.

Parametric Study for Terrain Interaction Analysis:

To comprehend the influence of diverse terrain material properties, a systematic parametric study is conducted. This involves creating a spectrum of scenarios with varying terrain characteristics, such as material stiffness, roughness, and cohesion. The purpose is to discern the nuanced impacts on the dynamic interplay between the tire and terrain.

Physics-Informed Neural Network (PiNN) Training:

Building upon the wealth of data generated by the Chrono FSI simulations, a Physics-Informed Neural Network (PiNN) is meticulously trained. This innovative approach harmonizes fundamental physics principles with advanced Deep Learning capabilities. The PiNN model is honed to predict terrain parameters based on the intricate interactions observed in the simulation data.

Comparative Performance Analysis:

A comprehensive comparison is undertaken to evaluate the PiNN model's performance against conventional methods. These methods encompass Multi-Layer Perceptron (MLP), stacked Long Short-Term Memory (LSTM), and stacked Gated Recurrent Unit (GRU) models. Through rigorous assessment, the accuracy, computational efficiency, and adaptability of the PiNN model are gauged.

Validation and Generalization Assessment:

Subsequently, the project focuses on validating the accuracy and robustness of the PiNN model. This validation involves applying the trained model to predict terrain parameters for scenarios beyond the training dataset. The alignment between predicted outcomes and actual data serves as a metric for assessing the model's generalization capability.

Formulas Used

Translational Motion Equations:
Surge (X-axis):

$$m \cdot \ddot{x} = F_x - X_r$$

Sway (Y-axis):

$$m \cdot \ddot{y} = F_y - Y_r$$

Heave (Z-axis):

$$m \cdot \ddot{z} = F_z - Z_r - m \cdot g$$

where,
m is the mass of the rover.
$\ddot{x}, \ddot{y}, \ddot{z}$ are the accelerations in the surge, sway, and heave directions, respectively.
F_x, F_y, F_z are the forces in the surge, sway, and heave directions, respectively.
X_r, Y_r, Z_r are the resistive forces opposing the rover's motion.
g is the acceleration due to gravity.

Rotational Motion Equations:
Roll (Roll-axis):

$$I_{xx} \cdot \dot{p} = L - (I_{yy} - I_{zz}) \cdot \dot{q} \cdot \dot{r}$$

Pitch (Pitch-axis):

$$I_{yy} \cdot \dot{q} = M - (I_{zz} - I_{xx}) \cdot \dot{r} \cdot \dot{p}$$

Yaw (Yaw-axis):

$$I_{zz} \cdot \dot{r} = N - (I_{xx} - I_{yy}) \cdot \dot{p} \cdot \dot{q}$$

Where,
I_{xx}, I_{yy}, I_{zz} are the moments of inertia around the roll, pitch, and yaw axes, respectively.
$\dot{p}, \dot{q}, \dot{r}$ are the angular velocities around the roll, pitch, and yaw axes, respectively.
L, M, N are the moments around the roll, pitch, and yaw axes, respectively.

Tire Forces and Moments Equations:
Longitudinal Force (Fx):

$$F_x = C_x \cdot \alpha \cdot F_z - D_x$$

Lateral Force (Fy):

$$F_y = C_y \cdot \beta \cdot F_z - D_y$$

Vertical Force (Fz):

$$F_z = W - F_{z\,roll} - F_{z\,pitch} - F_{z\,heave}$$

Rolling Resistance Moment (Mz):

$$M_z = B_z \cdot F_z - H_z$$

Where:

C_x, C_y, C_z are the tire stiffness coefficients in the longitudinal, lateral, and vertical directions.

α and β are the slip angles in the longitudinal and lateral directions, respectively.

F_x, F_y, F_z are the Longitudinal Force, Lateral Force

D_x and D_y are the damping coefficients in the longitudinal and lateral directions

W is the total weight supported by the tire.

$F_{z\,roll}, F_{z\,pitch}, F_{z\,heave}$ are the vertical forces due to roll, pitch, and heave motions.

B_z is the rolling resistance coefficient.

H_z is the rolling resistance moment.

Tire Slip Equations:

Longitudinal Slip (s_x):

$$s_x = (R\omega_r - V_x)/R\omega_r$$

Lateral Slip (s_y):

$$s_y = R\omega_r/V_y$$

Where:

R is the tire radius.

ω_r is the tire angular velocity.

V_x, V_y are the longitudinal and lateral velocities of the tire's contact point.

Tire Forces from Slip Angles:

Longitudinal Force (Fx) from Slip:

$$F_x = F_{x\,max} \cdot sin(C_x \cdot arctan(B_x \cdot s_x - E_x \cdot (B_x \cdot s_x - arctan(B_x \cdot s_x))))$$

Lateral Force (Fy) from Slip:

$$F_y = F_{y\,max} \cdot sin(C_y \cdot arctan(B_y \cdot s_y - E_y \cdot (B_y \cdot s_y - arctan(B_y \cdot s_y))))$$

Where:

F_{xmax}, F_{ymax} are the maximum longitudinal and lateral tire forces.

B_x, B_y are the stiffness coefficients for longitudinal and lateral slip.

C_x, C_y are the shape factors for longitudinal and lateral slip curves.

E_x, E_y are the curvature factors for longitudinal and lateral slip curves.

Basics of Smoothed Particle Hydrodynamics (SPH) Modeling:

Pressure Calculation (P):

$$P_i = \sum_j m_j (P_j/(\rho_j)^2 + P_i/(\rho_i)^2 + \Pi_{ij})W_{ij}$$

Viscous Forces (F_v):

$$Fvi = \mu \sum_j (m_j (V_{ij}/\rho_j) \nabla_i W_{ij})$$

Surface Tension Forces (F_{\sigma}):

$$F\sigma i = \sigma \sum_j (m_j (V_{ij}/\rho_j) \nabla_i W_{ij})$$

Where:

P_i is the pressure at particle i.

m_j is the pressure at particle j.

ρ_j is the density of particle j.

Π_{ij} is the artificial pressure term.

W_{ij} is the smoothing kernel between particles i and j.

μ is the dynamic viscosity.

V_{ij} is the velocity difference between particles i and j.

$\nabla_i W_{ij}$ is the gradient of the smoothing kernel with respect to particle i.

σ is the surface tension coefficient.

Terrain Stress Equations:

Normal Stress (σn):

$$\sigma_n =- K_\phi \cdot \phi - K_\psi \cdot \psi$$

Shear Stress (τ):

$$\tau =- \mu \cdot \sigma_n$$

Where:

ϕ represents the vertical displacement of the terrain.

ψ represents the lateral displacement of the terrain.

K_ϕ is the coefficient related to the vertical displacement of the terrain.

K_ψ is the coefficient related to the lateral displacement of the terrain.

μ is the coefficient of friction between the rover's tires and the terrain.

Terrain Strain Equations:

Normal Strain (ϵ_n):

$$\epsilon_n = \Delta h/h_0$$

Shear Strain (γ):

$$\gamma = \Delta x/h_0$$

Where:

Δh is the change in height of the terrain due to interaction.

h_0 is the original height of the terrain.
Δx is the lateral displacement of the terrain.

Neural Network Equations:

$$\mathrm{Loss}_{\mathrm{parameters}} = \frac{1}{N}\sum_{i=1}^{N}\left((\hat{\mu}_i - \mu_i)^2 + (\hat{\phi}_i - \phi_i)^2 + (\hat{\psi}_i - \psi_i)^2 + (\hat{K}_{\phi_i} - K_{\phi_i})^2 + (\hat{K}_{\psi_i} - K_{\psi_i})^2\right)$$

$$\mathrm{Loss}_{\mathrm{shear\_stress}} = \frac{1}{N}\sum_{i=1}^{N}(\hat{\tau}_i - \tau_i)^2$$

$$\mathrm{Loss}_{\mathrm{combined}} = \mathrm{Loss}_{\mathrm{parameters}} + \mathrm{Loss}_{\mathrm{shear\_stress}}$$

Results and Discussion

Model	RMSE
MLP	0.04
Stacked LSTM	0.01
Stacked GRU	0.05
PiNN	0.003

Table 1: Result comparison of various Deep Learning models for terrain estimation

The results underscore the superiority of the PiNN model in terrain parameter estimation. Not only does it achieve exceptional accuracy, but it also demonstrates minimal computational cost. Furthermore, the PiNN model exhibits a remarkable ability to handle data imperfections, making it robust and reliable for real-world applications. In conclusion, this technical report presents a comprehensive exploration of vehicle dynamics, tire-terrain interaction, SPH frameworks, and advanced Deep Learning models. The developed Physics-informed Neural Network (PiNN) model proves to be a groundbreaking solution for accurate terrain forecasting with the potential to revolutionize various industries reliant on precise terrain analysis. This study opens avenues for further research and innovation in the domain of vehicle dynamics and beyond.

Way Forward

One of the future studies is intended to develop an Multi-Body coupled 6DOF dynamic system having a Governing BEM-PiNN model and then to develop real-time adaptation strategies that allow the rover to adjust its behavior based on the continuously estimated terrain parameters. This could involve dynamic control algorithms that optimize rover actions to maximize performance and safety.