Automotive Crash Dynamics Modeling Accelerated with Machine Learning

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Abstract

Crashworthiness assessment is a critical aspect of automotive design, traditionally relying on high-fidelity finite element (FE) simulations that are computationally expensive and time-consuming. This work presents an exploratory comparative study on developing machine learning-based surrogate models for efficient prediction of structural deformation in crash scenarios using the NVIDIA PhysicsNeMo framework. Given the limited prior work applying machine learning to structural crash dynamics, the primary contribution lies in demonstrating the feasibility and engineering utility of the various modeling approaches explored in this work. We investigate two state-of-the-art neural network architectures for modeling crash dynamics: MeshGraphNet, a graph neural network that is widely employed in physics-based simulations, and Transolver, a transformer-based architecture with a physics-aware attention mechanism designed to maintain linear computational complexity with respect to geometric scale. Additionally, we examine three strategies for modeling transient dynamics: Time-Conditional, where the temporal state is directly parameterized by time; the standard Autoregressive approach, which recursively propagates predictions through time; and a stability-enhanced Autoregressive scheme incorporating rollout-based training to improve prediction accuracy and long-term temporal consistency. The models are evaluated on a comprehensive Body-in-White (BIW) crash dataset comprising 150 detailed FE simulations using LS-DYNA. The dataset represents a structurally rich vehicle assembly with over 200 components, including 38 key components featuring variable thickness distributions to capture realistic manufacturing variability. Each model utilizes the undeformed mesh geometry and component characteristics as inputs to predict the spatiotemporal evolution of the deformed mesh during the crash sequence. Evaluation results show that the models capture the overall deformation trends with reasonable fidelity, demonstrating the feasibility of applying machine learning to structural crash dynamics. Although not yet matching full FE accuracy, the models achieve orders-of-magnitude reductions in computational cost, enabling rapid design exploration and early-stage optimization in crashworthiness evaluation.

The code for this work is available at:

https://github.com/NVIDIA/physicsnemo/tree/main/examples/structural_mechanics

Introduction

In the modern automotive industry, the assurance of vehicle safety is not merely a design consideration but a fundamental engineering imperative. Crashworthiness, defined as the ability of a vehicle's structure to protect its occupants during an impact, is a primary driver of the design and validation process. This focus is enforced by stringent government regulations and amplified by consumer safety rating programs, which have created a competitive landscape where occupant protection is a key market differentiator. The engineering challenge of crashworthiness is profoundly complex, extending beyond simple structural strength. It involves the orchestrated management of kinetic energy during a collision, where specialized components like crumple zones are meticulously designed to deform in a controlled manner, absorbing impact energy and decelerating the vehicle to mitigate forces transferred to the occupant survival space.

The design of these safety-critical systems is an inherently iterative process. Engineers must evaluate a multitude of design variants, exploring the effects of geometric modifications, material selections, and component thicknesses on key performance indicators such as structural deformation, occupant compartment intrusion, and vehicle deceleration profiles [1]. Each design choice represents a compromise between safety, weight, cost, and manufacturability, necessitating a high volume of evaluations to converge on an optimal solution [2, 3].

High-Fidelity Finite Element Simulations

For several decades, the primary tool for virtual crashworthiness assessment has been high-fidelity Finite Element Analysis (FEA) [4]. FEA revolutionized automotive design by providing a virtual alternative to the prohibitively expensive and time-consuming process of building and destructively testing physical prototypes. The finite element method operates by discretizing a complex vehicle structure into a mesh of smaller, simpler elements. By solving the fundamental equations of motion and material behavior for each element, FEA can provide a detailed, full-field prediction of the dynamic, non-linear events that unfold during a crash, including large plastic deformations, buckling, and component interactions [5].

The historical development of FEA for crash simulation reflects a continuous pursuit of higher fidelity, driven by advances in computational power. Early, simplified approaches using spring-mass models gave way to sophisticated continuum models employing millions of shell and solid elements to represent a full vehicle with remarkable geometric detail. This evolution was critically enabled by the development of explicit time integration solvers, which are well-suited to handle the highly transient, non-linear dynamics characteristic of impact events, including complex contact and material folding phenomena that implicit solvers struggled with [4, 6].