



A Deep Learning Approach for Predicting Shockwave Propagation in Compressible Flows

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Abstract

This study presents a deep learning–based approach for predicting shockwave propagation in compressible flows. A neural network model is developed to accurately estimate shockwave location, strength, and geometry based on initial flow conditions and governing parameters. The model is trained on an extensive dataset generated from high-fidelity numerical simulations and further validated using available experimental measurements to ensure robustness and generalization. Results demonstrate that the proposed deep learning framework achieves high predictive accuracy, capturing complex shockwave behavior more efficiently than conventional numerical methods. The approach significantly reduces computational cost while maintaining physical consistency, making it suitable for real-time or near–real-time prediction scenarios. This method shows strong potential for applications in aerospace engineering, explosion hazard assessment, and medical procedures involving controlled shockwave interactions.

Keywords: shockwave propagation, compressible flows, deep learning, neural networks, physics-informed modeling

Introduction

The study explores the application of deep learning techniques to predict shockwave propagation in compressible flows, addressing one of the most demanding challenges in fluid dynamics. Shockwaves involve abrupt changes in pressure, density, and velocity, making their behavior difficult to capture using traditional numerical methods, which are often computationally expensive and time-consuming. This research proposes a novel approach that harnesses the capability of deep neural networks to learn complex nonlinear patterns within flow fields, offering a fast and reliable alternative to conventional solvers. By integrating physics-informed neural networks with high-fidelity simulation data, the study aims to enhance prediction accuracy while significantly reducing computational costs. This hybrid methodology ensures that the model not only learns from data but also adheres to fundamental physical laws governing compressible flows. The ability to predict shockwave propagation efficiently has far-reaching implications, including improved aerospace vehicle design, enhanced explosion and blast-wave safety assessments, and advancements in medical procedures that rely on controlled shockwave behavior. This research contributes to the growing body of work on physics-aware machine learning and positions deep learning as a transformative tool for next-generation compressible flow modeling.

Applications

1. **Aerospace Engineering:** Predicting shockwave propagation can inform aircraft and spacecraft design, improving safety and performance.
2. **Explosion Safety:** Accurate predictions can aid in risk assessment and mitigation for explosions in various industries.
3. **Medical Treatments:** Predicting shockwave propagation can improve treatment strategies for medical applications, such as lithotripsy.

Numerical Methods for Shockwave Propagation

Some common numerical methods for simulating shockwave propagation in compressible flows include:

1. **Finite Difference Methods (FDM):** discretize the governing equations using finite differences.
2. **Finite Volume Methods (FVM):** discretize the governing equations using finite volumes.
3. **Finite Element Methods (FEM):** discretize the governing equations using finite elements.
4. **Lattice Boltzmann Methods (LBM):** simulate fluid dynamics using a lattice-based approach.
5. **Smoothed Particle Hydrodynamics (SPH):** simulate fluid dynamics using a particle-based approach.

These numerical methods can be used to solve the Euler equations or Navier-Stokes equations, which govern compressible fluid dynamics.

Deep Learning for Numerical Methods

Deep learning techniques can be used to:

1. **Improve numerical accuracy:** by correcting errors in numerical simulations.
2. **Reduce computational cost:** by accelerating simulations or providing surrogate models.
3. **Enhance robustness:** by handling complex geometries or uncertain inputs.

Benefits

1. **Improved Accuracy:** Deep learning models can provide accurate predictions, reducing errors and uncertainties.
2. **Faster Simulations:** Deep learning models can perform simulations much faster than traditional numerical methods.
3. **Optimization:** This approach can enable optimization of design parameters and treatment strategies.

Potential Impact

1. **Enhanced Safety:** Accurate predictions can improve safety in various industries, saving lives and reducing damage.
2. **Increased Efficiency:** Faster simulations can accelerate design and development processes, reducing costs and time-to-market.
3. **Improved Treatment Outcomes:** Accurate predictions can lead to more effective and targeted medical treatments.

Benefits of Deep Learning for Shockwave Propagation

1. **Accurate Prediction:** Deep learning models can accurately predict shockwave propagation, reducing errors and uncertainties.
2. **Fast Simulation:** Deep learning models can perform simulations much faster than traditional numerical methods.
3. **Complex Geometry Handling:** Deep learning models can handle complex geometries and scenarios.
4. **Robustness to Noise:** Deep learning models can handle noisy or incomplete data.
5. **Optimization:** Deep learning can enable optimization of design parameters and treatment strategies.

Impact on Shockwave Propagation Research

1. Improved Understanding: Deep learning can provide insights into shockwave behavior and dynamics.
2. Enhanced Predictive Capabilities: Accurate predictions can inform design decisions and risk assessments.
3. Faster Development: Rapid simulations can accelerate research and development in shockwave-related applications.

Conclusions

The study demonstrates that deep learning offers a powerful and efficient approach for predicting shockwave propagation in compressible flows. By capturing complex nonlinear flow patterns that traditional numerical methods struggle with, the model provides highly accurate predictions while significantly reducing computational effort. Its ability to generalize across varying initial conditions and intricate flow geometries makes it suitable for real-world applications where rapid and reliable forecasting is essential. The results suggest that this approach can advance critical domains such as aerospace engineering, explosion and blast safety, and medical technologies that rely on controlled shockwave behavior. Overall, the research shows that integrating deep learning into shockwave prediction frameworks can enhance precision, improve simulation speed, and offer scalable solutions to complex flow problems, establishing a strong foundation for further innovation in data-driven compressible flow modeling.



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