

Using conservation laws to infer deep learning model accuracy of Richtmyer-Meshkov instabilities

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A Richtmyer-Meshkov instability (RMI) occurs when a shockwave amplifies perturbations at a material interface, causing large jet-like growths [1]. This phenomenon is similar to Rayleigh–Taylor (RT) instabilities that occur at the interface of fluids with different densities. An example RMI is shown forming in Fig. 1 at an interface, which results in a jet that deeply penetrates the neighboring material.



Figure 1: Snapshots of density in time increments of $0.1\mu\text{s}$ from left to right as an RMI forms.

To better understand how the initial geometry effects RMI growth, a thousand hydrodynamic simulations have been performed varying three initial geometric parameters. A deep learning model was trained to predict the full density and velocity fields from the geometric and temporal components. The model consists of the generator portion of [2] trained in regression.

The goal of the machine learning (ML) model is to quickly study RMI formulation within our geometric domain, which is only useful at untested configurations if the predictions are accurate enough. This work proposes error indicators based on basic conservation laws to quickly assess the ML prediction accuracy similar to the work in [3] where residual norm is used as an error indicator. Conservation of mass and momentum violations are shown to have weak correlations to traditional L^1 and L^2 errors. While there is a large potential for future improvements, this may present a reasonable solution for select applications.

References

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