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Neural Implicit Reduced Fluid Simulation

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Abstract

High-fidelity simulation of fluid dynamics is challenging because of the high dimensional state data needed to capture fine details and the large computational cost associated with advancing the system in time. We present neural implicit reduced fluid simulation (NIRFS), a reduced fluid simulation technique that combines a neural-implicit representation of fluid shapes and a neural ordinary differential equation to model the dynamics of fluid in the reduced latent space. Trajectories for NIRFS can be computed at very little cost in comparison to simulations for generating training data, while preserving many of the fine details. We show that this approach can work well, capturing the shapes and dynamics involved in a variety of scenarios with constrained initial conditions, e.g., droplet-droplet collisions, crown splashes, and fluid slosh in a container. In each scenario, we learn the latent implicit representation of fluid shapes with a deep-network signed distance function, as well as the energy function and parameters of a damped Hamiltonian system, which helps guarantee desirable properties of the latent dynamics. To ensure that latent shape representations form smooth and physically meaningful trajectories, we simultaneously learn the latent representation and dynamics. We evaluate novel simulations for conservation of volume and momentum conservation, discuss design decisions, and demonstrate an application of our method to fluid control.

CCS Concepts

• ***Computing methodologies*** → *Modeling and simulation; Computer graphics; Artificial intelligence;*

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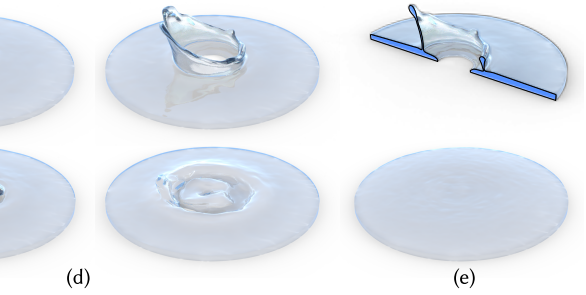
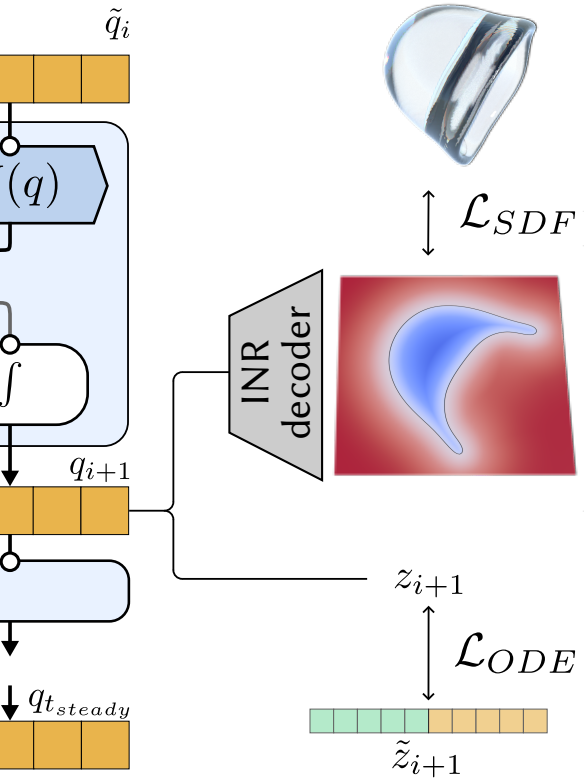


lity fluid simulation orders of magnitudes faster than conven-
ical initial condition, e.g., droplet position x and velocity v, to
damped Hamiltonian neural ODE (DHNODE) is integrated
q *in the trajectory, an implicit neural representation (INR)*
uency structures (e top) through. The correct steady state is



hieve training stability and convergence, we keep latent states
physical initial conditions of each full length simulation to
he buffer. Each DHNODE learns an energy function, a mass
from uniformly sampled latent states until (after) t_{steady}. For
rence between the rollouts and states in the buffer, and L_{SDF}
For the states rolled out at or beyond t_{steady}, L_{steady} measures
ates.