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FluidNeRF: a Machine Learning Based Approach for Physics Informed 3D Flow Tomography

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Abstract

We present a new multi-camera tomographic flow field reconstruction method, FluidNeRF, that exploits the ability of deep learning to solve inverse problems subject to multiple constraints. FluidNeRF is inspired by both the computer vision community, which developed the concept of neural radiance fields (NeRF), and the emergence of physics informed neural networks (PINNs) as an effective representation of real flow fields. In FluidNeRF, the volume of interest is represented by a deep neural network (NN) with spatiotemporal coordinates (x,y,z,t) as the input and volume luminance density (E) and flow field quantities (u,v,w,p) as the output. A ray tracing-based image model, which can include light scattering, emission, and absorption characteristics, is used to generate image projections from the NN volume estimate of E. A data loss term is defined as the difference between the NeRF projected image intensity and experimental images such that the trained NN represents the volume that best represents the experimental image data. Additional loss terms can be included based on optical flow equations or Navier-Stokes equations. The viability and performance of FluidNeRF is investigated using both synthetic and real experimental image data of a turbulent jet collected with 18-camera array. Synthetic experiments show that FluidNeRF produces more accurate 3D reconstructions and is more robust to noise than conventional discretized approaches. Real experiments demonstrate the feasibility of the method for practical applications. Compared to conventional, discretized approaches, the advantages of FluidNeRF are i) its compact, gridless representation of the volume that allows for more efficient scaling to more complex problems and larger domains, ii) the incorporation of physics loss terms for data assimilation, iii) the inherent ability to leverage recent advances in machine learning methods; and iv) the flexible nature of the approach for future applications.

Keywords: Physics Informed Neural Network (PINN), Neural Radiance Field (NeRF), Tomography, Data Assimilation, Experimental Methods