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MBZUAI

Department of Computer Vision and Metaverse Lab

Physics-Integrated Neural Fluid Reconstruction and Novel View Synthesis

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Administrative Summary

Faculty Supervising: Dr. J. Alejandro Amador Herrera **Department: CV and Metaverse**
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Project Duration: 2–3 semesters **Equipment:** Two GPU workstations (see §7).

1 Abstract

This project aims to develop a *physics-integrated neural framework* for reconstructing, simulating, and rendering dynamic fluid phenomena from monocular video input. Building upon *FluidNexus* [4], we unify neural rendering, physics-based fluid simulation, and video-conditioned reconstruction in a single differentiable system. Our model will reconstruct 3D fluid motion from a single video, perform novel-view synthesis, and enable future prediction via embedded Navier-Stokes constraints. The final objective is also to produce a top-tier publication at venues such as ACM SIGGRAPH, ICCV, or NeurIPS.

2 Background and Motivation

Neural scene representations (NeRF [2], 3DGS [1]) and differentiable fluid solvers (FluidNexus [4]) offer compact, learnable dynamics and photorealistic rendering, yet typically decouple physical simulation from video-based reconstruction. We target this gap by (i) conditioning a physically grounded Gaussian fluid representation on monocular video; (ii) enforcing Navier–Stokes residuals within a differentiable latent space; and (iii) achieving temporally consistent, physically plausible novel-view synthesis.

3 Model Overview

O1. Video-to-Fluid Reconstruction: Estimate 3D particle distributions (corresponding to a Lagrangian fluid model), densities, and velocities from monocular fluid videos using time-varying 3D Gaussian splats conditioned on optical flow and depth priors.

O2. Physics-Integrated Representation: Learn fields $\{\mathbf{u}(\mathbf{x},t), p(\mathbf{x},t), \rho(\mathbf{x},t)\}$ constrained by incompressible Navier–Stokes:

$$\begin{aligned} \partial_t \mathbf{u} + (\mathbf{u}\cdot\nabla)\mathbf{u} &= -\tfrac{1}{\rho}\nabla p + \nu\nabla^2\mathbf{u} + \mathbf{f}, \\ \nabla\cdot\mathbf{u} &= 0. \end{aligned} \tag{1}$$

O3. Forward Simulation and Prediction: Enable time extrapolation via differentiable advection and pressure projection in the learned latent dynamics.

O4. Novel View Synthesis: Render high-fidelity views using 3DGS with dynamic consistency across time.

4 Implementation

4.1 Monocular Video Reconstruction

We will extract pseudo-depth, optical flow, and silhouettes; represent the fluid via time-varying Gaussian primitives (centers, anisotropic covariances, opacities, radiance). Photometric losses will supervise differentiable splat rendering; with temporal regularization enforcing coherent motion.

4.2 Neural Physics Module

We will define a neural field $\Phi(\mathbf{x}, t) = \{\mathbf{u}, p, \rho\}$ subject to (1). Losses include photometric terms, physics-residual penalties, divergence constraints, and boundary conditions. We will develop implicit integrators and differentiable pressure projection to stabilize training, drawing on PINN-style formulations [3] and FluidNexus-style unified solvers [4].

4.3 Differentiable Rendering and Forward Prediction

Rendering will be based on 3DGS for real-time view synthesis. Forward evolution will apply learned differentiable advection and viscosity terms to predict future frames and synthesize videos from novel camera paths.

5 Preliminary Results

We have reproduced baseline FluidNexus experiments at reduced resolution and implemented a prototype that regresses velocity magnitude and density from single-view videos. These results were obtained on student laptops without CUDA acceleration, heavily constraining resolution, training duration, and ablation coverage.

6 Work Plan & Timeline

Semester 1	Foundations: literature review; dataset curation; baseline video-to-fluid reconstruction; replication of FluidNexus experiments. Deliverables: review & replication report; baseline code.
Semester 2	Integration: physics-constrained Gaussian representation; differentiable Navier–Stokes residuals; initial future prediction; system profiling. Deliverables: physics-aware prototype; internal demo.
Semester 3	Research & Publication: rendering fidelity and temporal consistency improvements; interactive simulation; full experiments; paper drafting for SIGGRAPH/ICCV/NeurIPS. Deliverables: paper submission, real-time demos, code release.

7 Resources and Equipment

To overcome current bottlenecks and reach publication-quality results, we require **two high-performance workstations** (one per subteam). Suggested configuration (per workstation): NVIDIA RTX 5090 (24 GB VRAM), 16-core CPU, 64 GB RAM, 4 TB NVMe SSD, Ubuntu + CUDA + PyTorch. These are essential for training differentiable renderers, running fluid simulations, and real-time 3DGS.

8 Team & Roles

Faculty Advisor: Dr. J. Alejandro Amador Herrera (Department of Computer Vision and Metaverse Lab).

UG Team: Ivan Kanev; Delyan Hristov; Stoyan Ganchev; Makar Ulesov.

9 Impact of Undergraduate Research

The project will introduce the team of four undergraduates into advanced research by engaging them with state-of-the-art vision, graphics, and physics simulation. The multidisciplinary workflow mirrors graduate-level research, preparing students for competitive graduate programs and top industry positions.

10 Deliverables

Open-source framework; research paper manuscript; demonstration videos; datasets and scripts; documentation for reproducibility and continued lab use.

11 Figures

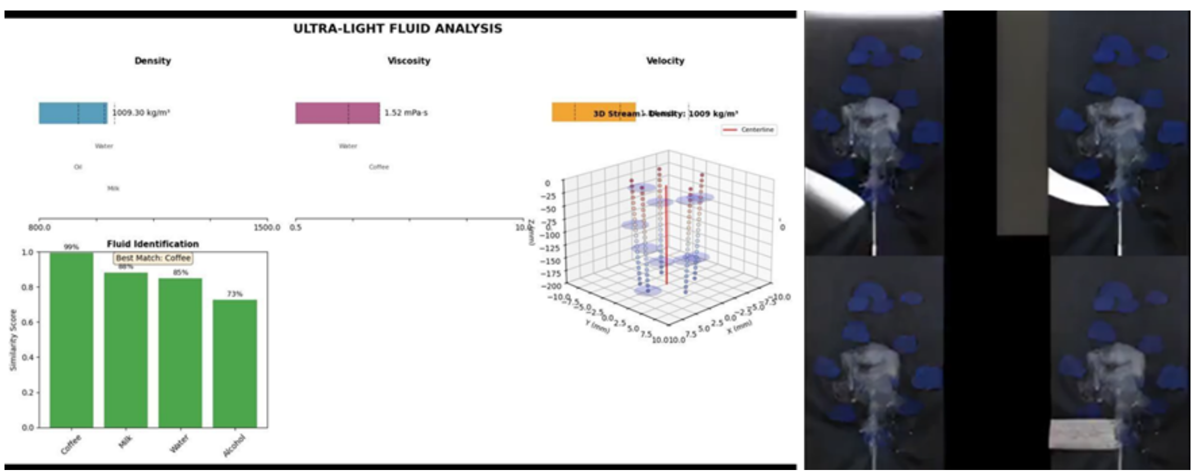

Figure 1: Showcase of preliminary results. Left: Prediction of fluid properties from monocular video, showing different predicted values for physical dofs (density, viscosity, and velocity). Right: Reproduction of low resolution experiment from FluidNexus, for a density-driven smoke dynamics.

References

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[2] B. Mildenhall et al., “Nerf: Representing scenes as neural radiance fields for view synthesis,” in *ECCV*, 2020.

[3] M. Raissi, P. Perdikaris, and G. E. Karniadakis, “Physics-informed neural networks: A deep learning framework for solving forward and inverse problems involving nonlinear partial differential equations,” *Journal of Computational Physics*, 2019.

[4] Y. Zhong et al., “Fluidnexus: A unified neural solver for fluid simulation and rendering,” in *ACM SIGGRAPH*, 2023.