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Holographic Particle Velocimetry via Gaussian-Parameterized Particles

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Abstract Text

1. Introduction

Particle tracking velocimetry aims to estimate the positions of particles in a fluid over time, providing information about both particle behavior and the characteristics of the fluid flow.

To this end, Digital Inline Holography (DIH) records the interference pattern between a reference wave and the light scattered by particles, yielding a 2D measurement that contains information about the underlying 3D volume [1].

The central task in DIH is to recover the 3D volume from the acquired 2D measurements, which can be formulated as an inverse problem. A straightforward solution is the Angular Spectrum Method (ASM) [2], which back-propagates each acquired measurement to different planes of the volume. Although ASM can produce reasonable reconstructions, these results often suffer from low axial resolution and severe artifacts [3].

Recent work mitigates these limitations by introducing hand-crafted [4] or data-driven priors [5, 6], but the resulting reconstructions can still exhibit morphological artifacts that are inconsistent with compact spherical particles. Moreover, these methods typically optimize a grid-based representation, which limits sub-pixel localization accuracy and consequently propagates errors to downstream particle tracking and velocity field estimation.

In this work, we directly model the scene as a collection of physically plausible spherical particles and optimize their continuous positions without relying on rigid grids. We show through simulations that this parameterization improves particle localization and velocity field estimation, and further demonstrate our method as a proof of concept on experimental data.

2. Method

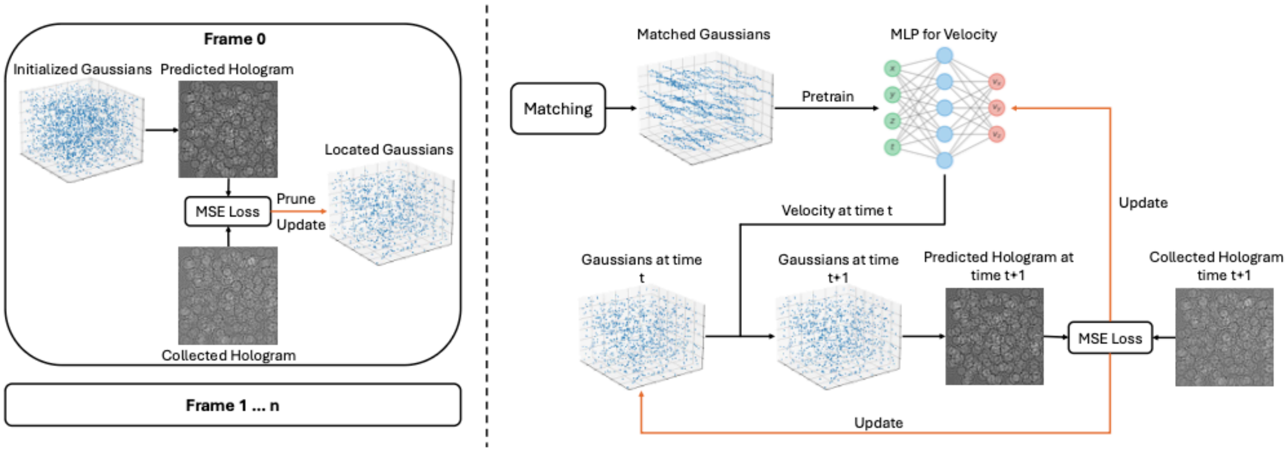

Fig. 1. Overview of the Proposed Algorithm. The first stage of algorithm (left) roughly identifies the number of particles in the volume and localizes them in each frame. The second stage of algorithm (right) refines this location estimate while simultaneously optimizing the flow model.

Particle Model. Inspired by differentiable point-based rendering [7], we model the particles using Gaussians. The scene is comprised of a collection of Gaussians $\boldsymbol{G} = \{G_i\}$, where each particle G_i is represented as an isotropic 3D Gaussian parameterized by its position $\mu \in \boldsymbol{R}^3$, radius r , and amplitude a :

$$G_i(x,y,z) = a \cdot \exp\left(-\frac{\|(x,y,z)-\mu_i\|^2}{2r^2}\right)$$

In practice, we assume all particles have identical radius r and amplitude a and only optimize the locations μ_i .

Flow Model. The Gaussians can effectively represent a static collection of particles; however, we also need to model their temporal displacement to reconstruct the particle flow. Given that implicit neural representations parameterized by multilayer perceptrons (MLPs) have recently shown great promise in modeling spatio-temporal flow fields [8], we use an MLP $f : \boldsymbol{R}^3 \times \boldsymbol{R} \rightarrow \boldsymbol{R}^3$ parameterized by weight θ to map spatio-temporal coordinates to velocity: $v = f(\mu, n; \theta)$, where $\mu = (x, y, z) \in \boldsymbol{R}^3$ denotes the spatial position, n denotes the frame, and $v \in \boldsymbol{R}^3$ is the predicted velocity.

Optimization. The optimization proceeds in two stages: we first roughly localize the particles in each frame and then refine this location estimate while simultaneously optimizing our fluid flow model.

In the particle localization stage, our goal is to identify the correct number of Gaussians and roughly identify their locations in each frame. We randomly initialize a sufficiently large number m of Gaussians and optimize their locations and amplitudes to match the observed data:

$$Loss = \frac{1}{m}\left|\Pi(\mathbf{G}_n) - I_{real}^{(n)}\right|^2$$

Π is a differentiable forward model which simulates 2D holograms by propagating the optical field generated by 3D particles via the angular spectrum method. $\boldsymbol{G}_n$ is the collection of the Gaussians at frame n , characterized by positions $\{\mu^*_i\}$ and the amplitudes $\{a^*_i\}$, which are both optimized jointly in this stage. After a sufficiently large number of iterations, Gaussians are pruned if their amplitude is below a threshold; this process allows us to determine the best number of Gaussians to describe our data. The remaining Gaussians' amplitudes are then all set to a known value and fixed. In subsequent optimization stages, only the positions $\{\mu^*_i\}$ will be updated.

Next, we use our localized Gaussians to reconstruct the dynamic flow. The same Gaussians that appear in subsequent frames are matched using a Hungarian matching algorithm. Matched pairs whose distance is larger than a threshold are discarded. This provides a good initial velocity value for the MLP to learn. Then, we jointly optimize the weights θ of the MLP and the positions $\{\mu_i\}_n$ of the Gaussians at frame n , using the loss function:

$$Loss = \left|\Pi(\mathbf{G}^*_{n+1}) - I_{real}^{(n+1)}\right|^2$$

Here, $\boldsymbol{G}^*_{n+1}$ represents **not** the learned Gaussian location at time $n+1$, but instead the learned Gaussian at time n plus the displacement represented by the MLP f :

$$\mathbf{G}^*_{(n+1)} = \left\{a \cdot \exp\left(-\frac{\|(x,y,z) - [\boldsymbol{\mu}^*_n + f(\boldsymbol{\mu}^*, n; \boldsymbol{\theta})]\|^2}{2r^2}\right)\right\}$$

This joint optimization procedure encourages both the Gaussians to settle in consistent locations from frame to frame and for the MLP to accurately represent the fluid flow.

3. Results

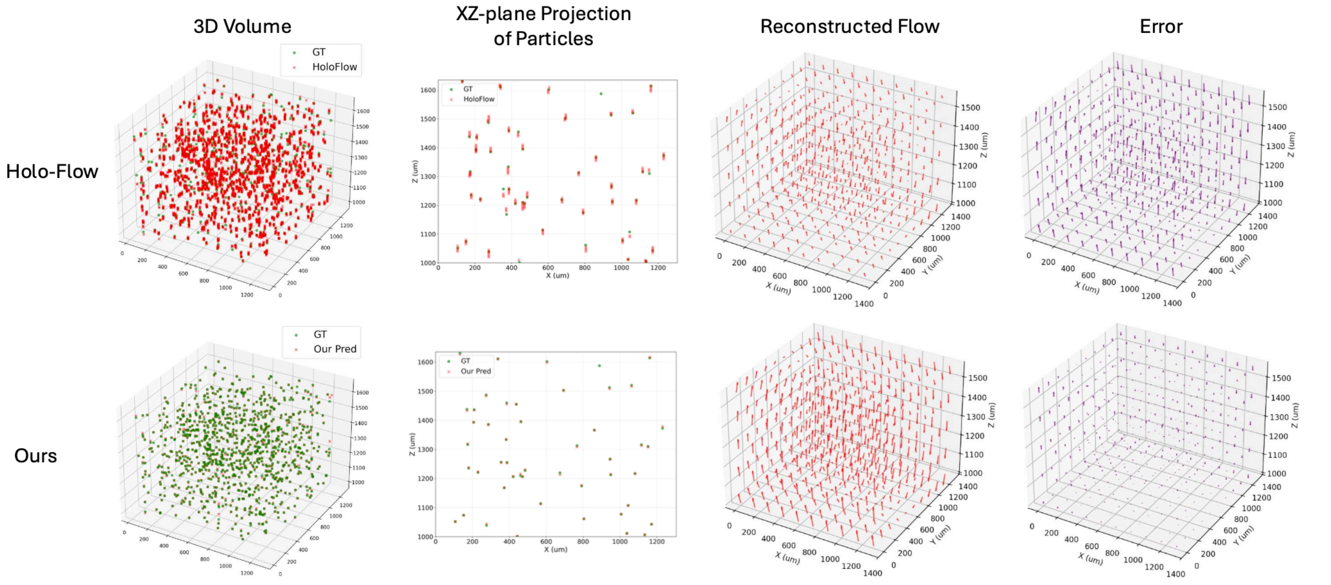

Fig. 2. Particle Localization Results on Simulated Data. 3D localization results with projections into the XZ-plane (left) and learned flow field and error relative to ground truth (right). Compared to the baseline method Holo-Flow [4], our method shows superior particle localization and smaller error in velocity field estimation.

We first evaluate our method on simulated DIH data. We generate a sequence of three holograms, each with a resolution of 256 × 256 pixels and a pixel size of 5 µm. The scene consists of 1000 particles randomly distributed within a 1280 µm × 1280 µm × 635 µm volume. A zero padding of 5 pixels is applied around the hologram. The sensor plane is 1 mm away from the volume, and the illumination wavelength is 0.660 µm. In simulation, all particles are set to have the same radius (2.5 µm) and amplitude (1.0). In the second and the third frame, the particles' location is computed based on the first frame and a simulated vortex flow: $v = (0, z, -y)$. As shown in Fig. 2, our algorithm shows significant performance improvement over the Holo-Flow baseline [4] in particle localization. While the baseline has high false-positive rates, our approach closely matches the ground truth. Furthermore, the reconstructed velocity field and the vector error maps show negligible deviation from the ground truth, which is also superior to the baseline.

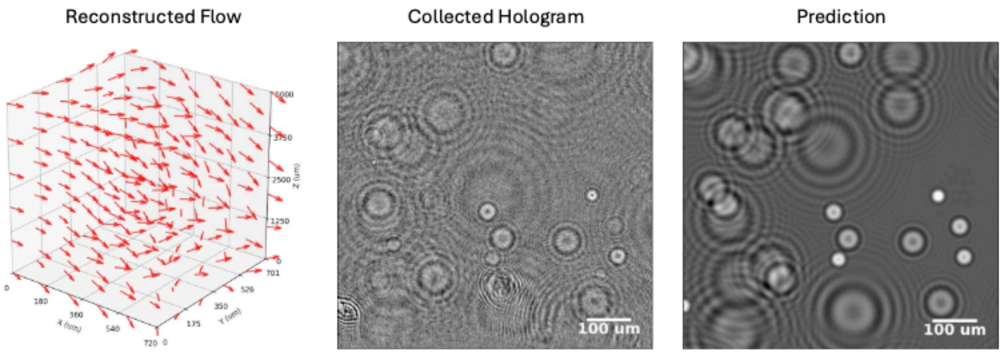

Fig. 3. Flow reconstruction results and hologram comparison on experimental data. Our method produces a plausible, spatially coherent flow and largely matches the collected hologram data, though a few beads are not captured.

To validate our approach under real experimental conditions from [9], where polystyrene beads are undergoing feeding currents of aquatic microscopic organisms (*Vorticella*), we apply the proposed method to experimentally captured holographic data. As shown in Fig. 3, the reconstructed velocity field exhibits a coherent dominant flow direction, consistent with the underlying physical flow. Besides that, the hologram synthesized by forward rendering the reconstructed 3D particle field closely matches the captured hologram, consistent with the measurement. However, as also evident from the predicted hologram in Fig. 3, the current method occasionally fails to recover particles located at extreme depths. Improving reconstruction in these regions will be the focus of future work.

Keywords

Digital Inline Holography; Particle Tracking Velocimetry; Volumetric Reconstruction; Computational Microscopy