Machine Learning Based Digital Holographic Microscopy

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Abstract

In this report, we briefly described the experimental details used for recording the digital hologram. We had reproduced the previous works and provided their results along with the bit of explanation about the LodeSTAR model. We also showed the produced synthetic data in comparison with the experimental image with their pixel intensity hologram. Future work has been provided along with the difficulties that are currently being faced.

1 Introduction

Digital Holographic Microscopy (DHM) is a technique that can be used to store information about the particles in 3 dimensions along with various other properties. The interference pattern, which is called the hologram, is created using a coherent illumination source like a laser. Using a beam splitter, the laser is split into two parts, one of which goes and interacts with the specimen called the object beam, and the other is the reference beam, which interferes with the object beam to create holograms that carry the phase information. In this project, we aim to track the particles' position in 3D and size in the range of micrometres in a microfluidic device using deep learning algorithms on the DHM data of the particles.

The particles, in general, follow Brownian motion in a fluid. But when the particle comes under a local thermal perturbation, it starts to move due to effects like convective flow, thermo-osmotic flow, thermoviscous flow, and thermophoresis in the fluid. when the fluid transport is dominant, the particle trajectories directly report on the fluid dynamics. Achieving this local thermal perturbation will be explained in the experimental setup section. This local thermal perturbation at the microscale can be used to achieve long-range transport, which can lead to changes in mm scale for both fluid and particle dynamics. The motivation behind the work is that this long-range movement of particles and fluids can be used in lab-on-a-chip technology for the mixing of samples and fluids, which is still a big hurdle. It is very difficult to control the fluid dynamics on such a small scale as the available external fluid controllers are pretty bulky and cannot be used on such small devices. There is an apparent mismatch in the size.

2 Experimental Setup in Brief

The experimental setup consists of a flow cell system consisting of two coverslips spaced by a silica space of known length, and the cell contains water (n = 1.333) and silica particles having a diameter of 1.5μm with refractive index (n) = 1.4645. The lower slip contains the uniform distribution of gold nanorods (AuNRs) on which we shine a light to produce local thermal perturbation. The flow cell is illuminated using the pump-probe technique. The AuNRs are illuminated by a pump beam with a wavelength of 780 nm to create heat, and the DHM is done using a probe beam of 465 nm. CMOS

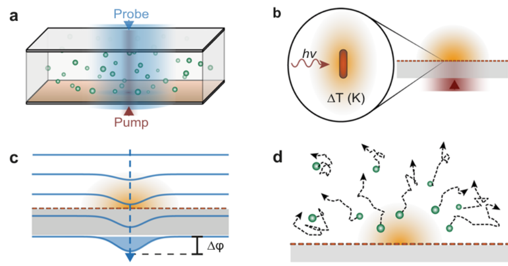

Figure 1: Schematics of Experimental Setup

camera with a resolution of 0.106μm/pixel with a magnification of 55x and a numerical aperture (NA) of 0.65 was used to record the hologram. The experiment utilizes a label-free thermometry method that identifies small phase changes caused by temperature-dependent variations in the refractive index of the imaging medium. These changes accumulate as the incident wavefront traverses the sample, resulting in an overall difference in optical path length. The fluid dynamics are determined by tracking the movement of tracer particles in three dimensions. B. Ciraulo et al. developed a custom off-axis digital holographic microscope that integrates wavefront sensing and 3D particle-tracking velocimetry, operating in a pump/probe setup. Detailed information about the experimental setup and the achievement of long-range transport can be found in the reference [1].

3 Reproduced work:

Similar work has been done by Midtvedt et al. [2,] using two different models: one is U-Net, which is a supervised learning model, and the other is Localization and detection from Symmetries, Translations And Rotations (LodeSTAR), which is a self-supervised model.

The LodeSTAR model has achieved better results using the same dataset than the U-Net for the same task. The results they have achieved compared to the existing numerical algorithms have been shown in fig.(4,5) and their loss in fig.(2,3).

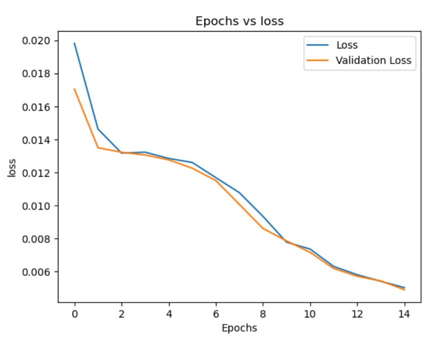

Figure 2: For U-Net

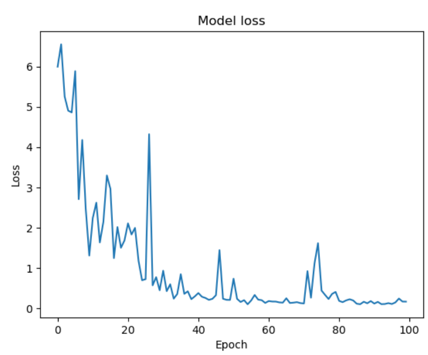

Figure 3: For LodeSTAR

LodeSTAR is a system designed to detect microscopic objects by leveraging inherent symmetries. It operates on the principle of equivariance, meaning that transformations applied to the object image, such as translations, rotations, and reflections, result in corresponding transformations in the object's predicted position. This allows LodeSTAR to accurately locate the centre of an object, even if its absolute position is unknown. The system achieves this by training a neural network to establish an exact correspondence between the transformations applied to the input image and their effects on the output prediction. In addition to the aforementioned capabilities, LodeSTAR can also process holographic images. These images can be moved to various planes or different axial positions from the focal plane using Fourier transforms. This introduces another form of equivariance that LodeSTAR can learn, similar to the equivariances on the plane. This means that LodeSTAR can adapt

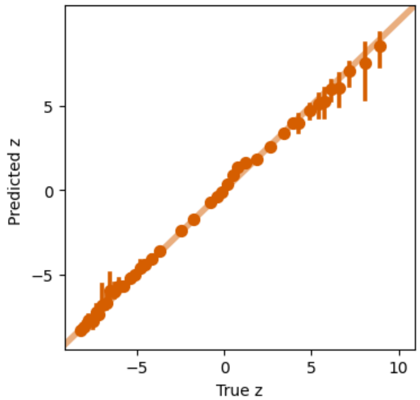

Figure 4: LodeSTAR output vs Numerical Algorithm predicted z

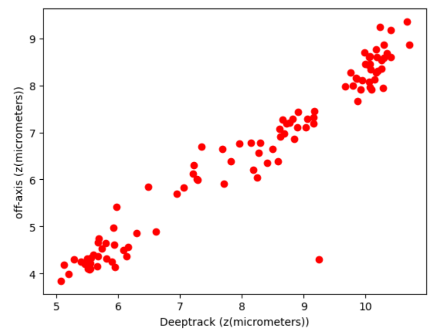

Figure 5: U-Net output vs Numerical Algorithm predicted z

to changes in the axial position of the object image, further enhancing its ability to locate microscopic objects accurately. The precise mathematical explanation of the LodeSTAR model can be found in the method section of ref.[3].

3.1 Experimental details, Data representation and preprocessing:

The experimental data [4] used in the models above have very different optical details than ours, on which the above models and results have been shown. In their dataset, the particles have a size of 190nm with a refractive index of 1.45. Their hologram has a resolution of 0.345 μ/m, and the Δ z = 28μm. In the U-Net model, the no. of features, which are the no. of the output of the model, is defined as Δz/resolution.

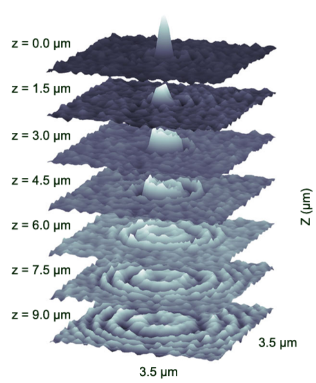

Figure 6: Propagation of focal plane in z

In order to find the 3D position from the 2D images, the interference pattern was reconstructed into the Fourier space, which has been used for analysis. Their data representation was done in the form of a Matlab file containing the reconstructed field. These traces contain the Region of Interest (ROI) and position in x,y, and z, which were evaluated using numerical algorithms and the mapping matrix. For U-Net, each particle's ROI was selected and cropped into a 64x64 image size before giving it to the model. The holographic image can be moved to various planes, meaning different axial positions from the focal plane, by using Fourier transforms. This introduces an equivariance that LodeSTAR can learn, similar to the equivariances on the plane. By training on the image in the top slice, i.e., z =

0, as shown in Fig. (6), LodeSTAR learns to identify the location of the polystyrene spheres in 3D space. Here, the measured vertical position is represented as the distance in the image.

4 Synethetic Images

This section will show the images generated to train the U-Net. Before giving images to the model, we must ensure that the pixel-intensity histograms of simulated and experimental images are the same. DeepTrack[2] framework produced the simulated images, brightfield microscopy, and other optical details. The results are shown in fig.(7)

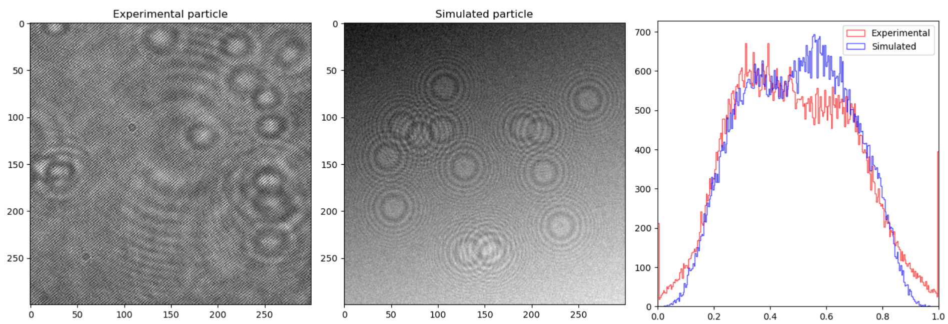

Figure 7: Pixel intensity of Histogram

5 Future Work:

The main problem currently we are facing is of the data representation. There is little information provided in the literature on reproducing this processed field, tracing, and mapping. Our primary goal is to find an appropriate way to present the data, which can be given to the model to get the predictions. One problem with the U-Net is that, for our data, the number of features is 377, which is same the number of output nodes in the model, which is relatively high, as we cannot train the model due to GPUs having less memory. Once we can train the model to get the predictions and close the true values, we will try fine-tuning the model for better predictions and make it more robust.

References

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