Machine Learning Based Digital Holographic Microscopy

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Experimental Setup

To track the particle's position in 3D using Digital Holographic Images. Particles move due to the heat produced by surface plasmon resonance heating.



Figure 1. Plasmon heating opto-fluidic platform $^{\left[1\right] }$

DataSet Comparison





Labelling and Prediction

I give the model image as input of tensor (64,64,1). The model predicts the label for that particular image and provides the output with tensor as (1,64,64, Number of bins [122]).



Figure 9. Image for which labels are predicted below

Figure 8. Synthetic image labelling

To test the model and ensure it is learning, we create spherical labels of particles, and the model tries to predict their labels at each epoch and minimise the loss function.

Training of the model was done on 3000 images and testing on 256 images. The total number of parameters in the model was 57.6M.





Figure 4. Experimental image



Figure 5. Synthetic image

Synthetic images are generated using the DeepTrack framework. To ensure the synthetic images are similar to the experimental images, match the intensity profile of both the images.

U-Net Model

U-Net is a convolutional neural network (CNN) architecture commonly used for image segmentation tasks. The architecture consists of encoder-decoder and skip connections for the direct flow of information.





Current Problems

- Too many particles in a single frame
- Particles are in defocus because the model does not predict any label.
- Due to the labels of many particles in a single frame, the centroid algorithm predicts the wrong location of the particle.

Possible Solutions and Future Work

- Get the focused frame of particles using numerical methods to propagate the fields in z and then apply unet by further cutting down the frames.
- Use of transformers to solve the problem. DETR is a detection transformer developed by Facebook that is used for object classification.
- DETR^[3] uses bipartite matching loss to get the predictions. We can leverage this bipartite matching loss function to create a model where each bin in the z-axis will be defined as a



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Figure 6. Schematics of the U-Net model

separate class. Now, each particle will be directly mapped into a bin.





Figure 11. DETR

Previous Work

Figure 3. synthetic image



Figure 7. Particle traces Z position traces by ML model and numerical methods

References

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CS460 - Machine Learning Project

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