3D Reconstruction of Atom Cloud in the Imaging System for a novel MAGIS-100 Atomic Interferometer

Fellow: Patin Inkaew
Mentors: Ariel Schwartzman, Murtaza Safdari, Maxime Vandegar, Michael Kagan

1 Introduction

Recently, atomic interferometers and atomic clocks have achieved higher sensitivity and precision, allowing physicists to utilize atomic interferometers to study precision physics: highly-precise testing of fundamental laws of physics. Furthermore, atomic interferometers can be used to search for new elusive particles, and new forces, as well as to detect gravitational wave. Unlike current gravitational wave detectors, such as LIGO and VIRGO, atomic interferometers will have significantly smaller sizes in the order of meters, compared to kilometers. The Matter-wave Atomic Gradiometer Interferometric Sensor (MAGIS-100) [1] is a novel proposed atomic interferometer being constructed at Fermi National Accelerator Laboratory. The MAGIS-100 experiment will use the latest technology in atomic interferometry with a much more complex and sensitive sensor to probe and test quantum mechanical coherence fluctuations from a wide variety of sources, including sources from large macroscopic distances.

The atomic interferometers utilize the interference of matter waves. In an atomic interferometer, compared to light, a cloud of atoms is the media used to measure the interference phase difference between paths. Laser light is shot into the atom cloud at the right moment to split atoms into two quantum states, acting as a beam splitter. Subsequent laser light is used to reflect the phase, acting as a mirror. By directing the laser lights to the cloud at the precise timing, several types of matter-wave interferometers resembling the light interferometers, including Mach–Zehnder and conjugate Ramsey-Borde, can be constructed.

3D reconstruction of the atom cloud is a crucial part of the sensing mechanism of an atomic interferometer to measure the phase difference. Interference patterns collected from multiple cameras at different views are taken and used to reconstruct the 3D locations of atoms and the 3D shape of the cloud. This task is particularly challenging because 2D images of interference patterns are represented as the density of atoms and do not have distinct imagery features, such as edges or color gradients. Traditional 3D reconstruction methods used in computer vision cannot be straightforwardly applied. Another limitation includes mechanical restrictions: cameras are fitted on the apparatus and the experimental setup restricts the position and number of cameras. The currently proposed design of the MAGIS-100 detector has only six camera views which pose an underdetermined problem for the recovery of 3D atom cloud from 2D projection images.

In this project, we will investigate the performance of several neural network-based methods for the 3D reconstruction of atom clouds. The brief details of the dataset proposed reconstruction methods, and evaluation metrics are discussed in the next section. We hope this comparative study will facilitate the selection of 3D reconstruction algorithms which will be used in the imaging system of the upcoming MAGIS-100 experiment.

2 Methods

2.1 Dataset

In this project, we will use a simulation dataset of a 3D atom cloud and corresponding 2D projection images. The MAGIS-100 group led by Professor Ariel Schwartzman at SLAC National Laboratory has developed a differentiable optics simulation framework (diffoptics) based on ray-tracing. We will use this package to configure the scene similar to the proposed setup of MAGIS-100's imaging system. The motivation is that since the optics simulator is differentiable, we can use the real experimental data collected to improve the simulation to lower the simulation-to-real gap through a learning strategy with gradient-based optimization methods similar to training deep network model. This learning process is similar to that of differentiable physics engine used in robotics research. Another advantage of simulation data is that we have access to the 3D density ground truth of the atom cloud which can be used to evaluate the reconstructed output from the model. In the real experiment, it is often impossible to recover the 3D structure ground truth.

2.2 Proposed Reconstruction Methods

As discussed before, this project will focus on neural-based reconstruction methods. We represent the density of the atom cloud in a 3D voxel grid. All reconstruction methods take in the 2D projection images together with camera pose parameters and try to reconstruct the corresponding 3D density of the atom cloud. The first method, Voxel reconstruction, is already developed, being tested extensively, and proven to reconstruct high-quality 3D atom cloud density. The remaining two methods are proposed and will be investigated with their performance benchmarked with Voxel reconstruction.

2.2.1 Voxel Reconstruction

This method is similar to Google's DeepDream and other works in deep generative model [2, 6]. First, the 3D density of the atom cloud is randomly initialized. Then, we use this density to produce 2D projection images through diffoptics simulation. Then, we compute the loss between 2D projection images and reconstructed images, referred to as a reprojection error. Since the simulator is differentiable, we can compute the gradient of the objective function and we use this gradient to nudge the input density to the correct 3D density. The voxel reconstruction method is currently studied at the SLAC MAGIS-100 group. and is shown to be able to produce a high-quality reconstruction. The main advantage of this method is the low memory requirement since there is low additional memory needed in the model and simulated view generation is already loaded for reprojection error computation. However, the disadvantage is that this method does not utilize other training data points, so this method is highly dependent on the quality of the obtained single datapoint, and the reconstruction can be easily overfitted.

2.2.2 Neural Radiance Field

Neural Radiance Field (NeRF) is a class of neural network architecture to estimate radiance field $L(\mathbf{x}, \omega)$ which is the power per area per solid angle as a function of 3D position $\mathbf{x}$ and solid angle ω. NeRF is used to solve novel view synthesis: given some 2D camera views, generate views at different angles. To produce new camera views, the model must capture the information on the 3D positions of the real world. NeRF is originally introduced in [4] and there have been many studies on other variations to improve the performance as well as training time. The most recent study [5] shows a significant improvement in training speed. An alternative method to estimate the radiance field without a neural network has also been studied [7]. Once the radiance field has been estimated, we can use an integrator to reconstruct the 3D density.

Currently, since research related to NeRF has been extensively studied in recent years, we propose to investigate the performance of NeRF and its variations to tackle the 3D reconstruction of atom clouds.

2.2.3 Neural Volume Rendering

Neural Volume Rendering is another class of neural network taking in 2D views and estimating 3D positions and density based on the volumetric rendering of a 3D scene. The most recent work which improves the performance and speed includes [3].

This is another method we propose to probe its performance in reconstructing the 3D atom cloud for the MAGIS-100 experiment.

2.3 Evaluation Metrics

Finally, evaluation metrics are another aspect of the project. Currently, the model is tested with visual comparison as a qualitative measurement. Reprojection error, an error measure between the ground truth 2D projection images and regenerated 2D projection, is the popular metric used in computer vision research. This error is also used to train the reconstruction model. However, since different 3D atom clouds can generate the same 2D projection views as the number of camera views is highly limited (six, in the case of MAGIS-100), there is high degeneracy. Additional loss functions, such as enforcing the smoothness of atom cloud, must be used during training. For testing, since we use simulated data, we can compare 3D ground truth data as additional metrics. Dense map posterior (DMP) [8] is a proposed metric to evaluate the quality of 3D reconstruction without ground truth, allowing a seamless transition from simulation data to real experimental data.

3 Project Timeline

- Before summer (before 06/18/22): discussion of the class project results, kick-off meeting for the summer, goal setting, hand-on and code base walk-through, development environment setup, literature reviews on statistical analysis and recent work on neural reconstruction methods including NERF-related architecture to improve training time and potentially, metalearning and hypernetwork.
- Week 1-2 (06/19/22 - 07/02/22): building softwore pipeline to extract useful information, for example phase difference, from learned neural network architecture, such as voxel reconstruction method
- Week 3-4 (07/03/22 - 07/16/22): continue on physical information extraction pipeline. If time permitted, studying the ability of the neural network to lean cloud aberrations, such as smearing and noise.
- Week 5-6 (07/17/22 - 07/30/22): perform statistical analysis and quantifying the ability of the system to retrieve the phase and comparison with standard setups: improvement with multiple lenses setup compared to single lenses.
- Week 7-8 (07/31/22 - 08/13/22): continue statistical analysis on the performance, optimization of the training time with recent NERF-based architecture
- Week 9-10 (08/14/22 - 08/27/22): continue statistical analysis and optimization of the training time, project wrap-up, finalize README on repository, write report, prepare for presentation

Deliverables: project report, and poster or presentation (if appropriate)

References

[1] M. Abe, P. Adamson, M. Borcean, D. Bortoletto, K. Bridges, S. P. Carman, S. Chattopadhyay, J. Coleman, N. M. Curfman, K. DeRose, T. Deshpande, S. Dimopoulos, C. J. Foot, J. C. Frisch, B. E. Garber, S. Geer, V. Gibson, J. Glick, P. W. Graham, S. R. Hahn, R. Harnik, L. Hawkins, S. Hindley, J. M. Hogan, Y. Jiang (), M. A. Kasevich, R. J. Kellett, M. Kiburg, T. Kovachy, J. D. Lykken, J. March-Russell, J. Mitchell, M. Murphy, M. Nantel, L. E. Nobrega, R. K. Plunkett, S. Rajendran, J. Rudolph, N. Sachdeva, M. Safdari, J. K. Santucci, A. G. Schwartzman, I. Shipsey, H. Swan, L. R. Valerio, A. Vasonis, Y. Wang, and T. Wilkason. Matter-wave atomic gradiometer interferometric sensor (magis-100). *Quantum Science and Technology*, 6(4):044003, Jul 2021.

[2] G. Kim, T. Kwon, and J. C. Ye. Diffusionclip: Text-guided diffusion models for robust image manipulation, 2021.

[3] D. B. Lindell, J. N. P. Martel, and G. Wetzstein. Autoint: Automatic integration for fast neural volume rendering, 2020.

[4] B. Mildenhall, P. P. Srinivasan, M. Tancik, J. T. Barron, R. Ramamoorthi, and R. Ng. Nerf: Representing scenes as neural radiance fields for view synthesis. In *European conference on computer vision*, pages 405–421. Springer, 2020.

[5] T. Müller, A. Evans, C. Schied, and A. Keller. Instant neural graphics primitives with a multiresolution hash encoding. *arXiv:2201.05989*, Jan. 2022.

[6] Y. Song, J. Sohl-Dickstein, D. P. Kingma, A. Kumar, S. Ermon, and B. Poole. Score-based generative modeling through stochastic differential equations, 2020.

[7] A. Yu, S. Fridovich-Keil, M. Tancik, Q. Chen, B. Recht, and A. Kanazawa. Plenoxels: Radiance fields without neural networks, 2021.

[8] G. Zhang and Y. Chen. A metric for evaluating 3d reconstruction and mapping performance with no ground truthing, 2021.