

Simulation of the multi-view imaging system with differentiable ray tracing

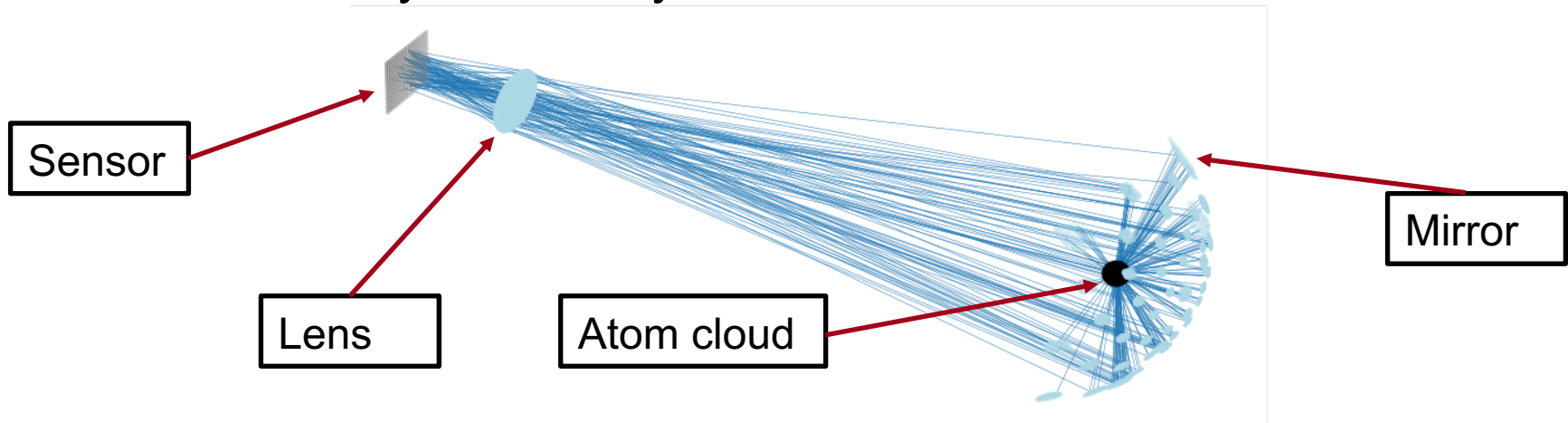
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- **System insights:**
 - Provides image modeling for potential system design.
 - Design optimization.
- **Data analysis (i.e. parameter inference):**
 - Data / simulation comparison.
 - Systematic uncertainty modeling.
 - 3d reconstruction & parameter estimation.

Approach

- A simulator to map photon emission from the atom cloud to a multi-view image on sensor.
- Physics-driven approach to rendering images on sensor.
 1. Stochastic emission from the atom cloud.
 2. Trace light rays through the optical system.
 - Includes interaction with lenses, mirrors, apertures, etc.
 3. Trace rays until they hit the sensor.

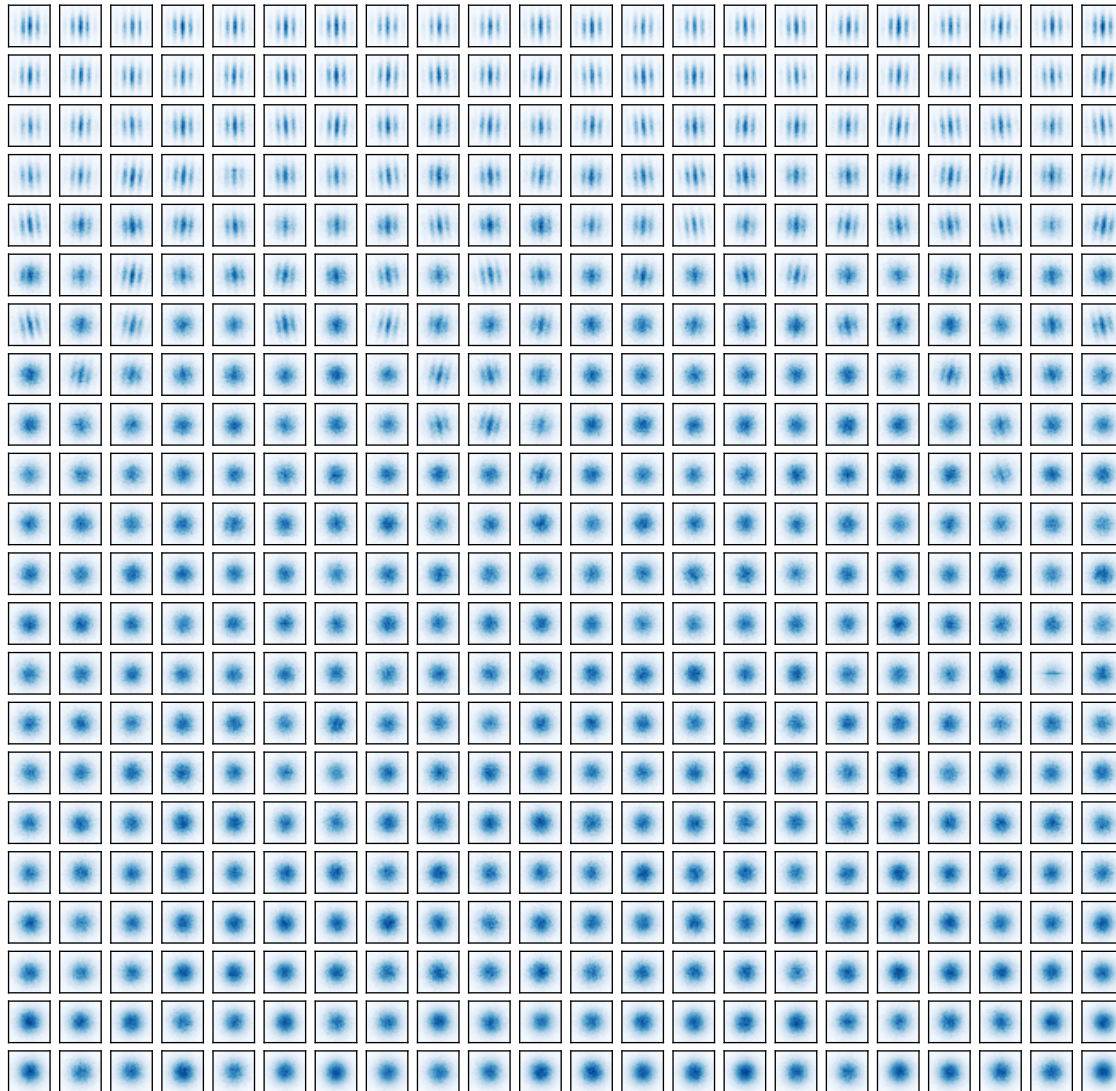


- Implemented in Python within automatic differentiation framework (PyTorch).
- Every traced ray is differentiable end-to-end.
 - Enables gradient descent from images back to atom cloud / system properties for optimization & parameter estimation.
 - Natively ready for interfacing with machine learning algorithms & pipeline.
- High throughput.
 - Vectorizable – trace many rays at once.
 - Parallizable – over multiple devices.
 - Support on CPU / GPU.
 - Just-in-time (jit) compilation for reducing computational time.

Simulator's fidelity

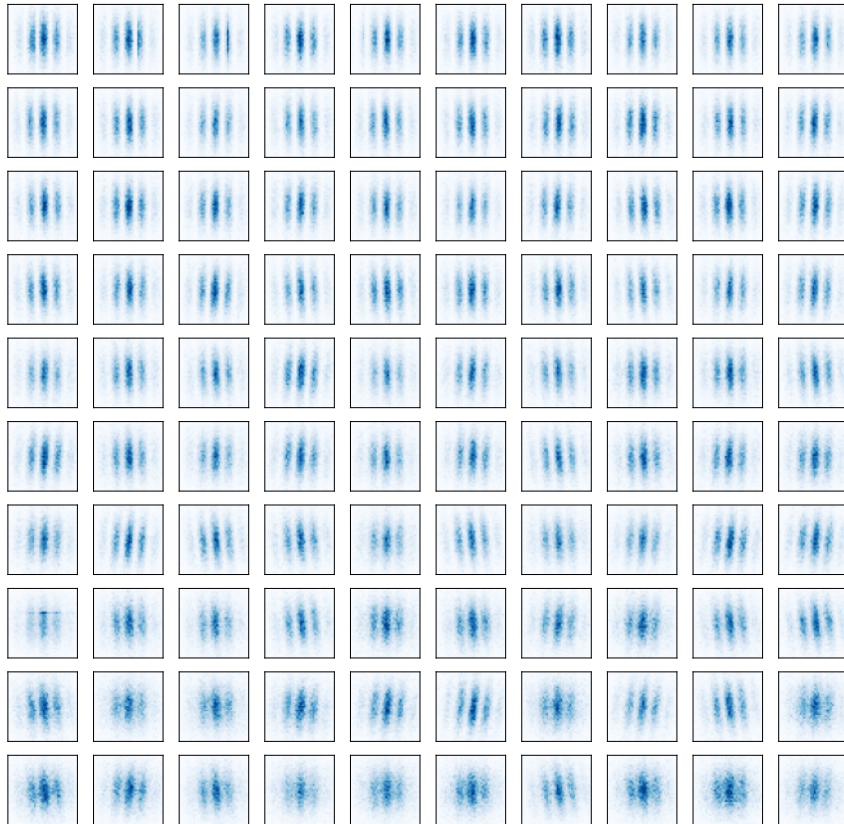
- Currently using perfect lens / mirror / sensor approximation.
 - Thin lens model, no readout noise, no quantum efficiency, ...
- Easy to add complexity and noise to the system.
 - Which should we add first?

Simulated views (1)

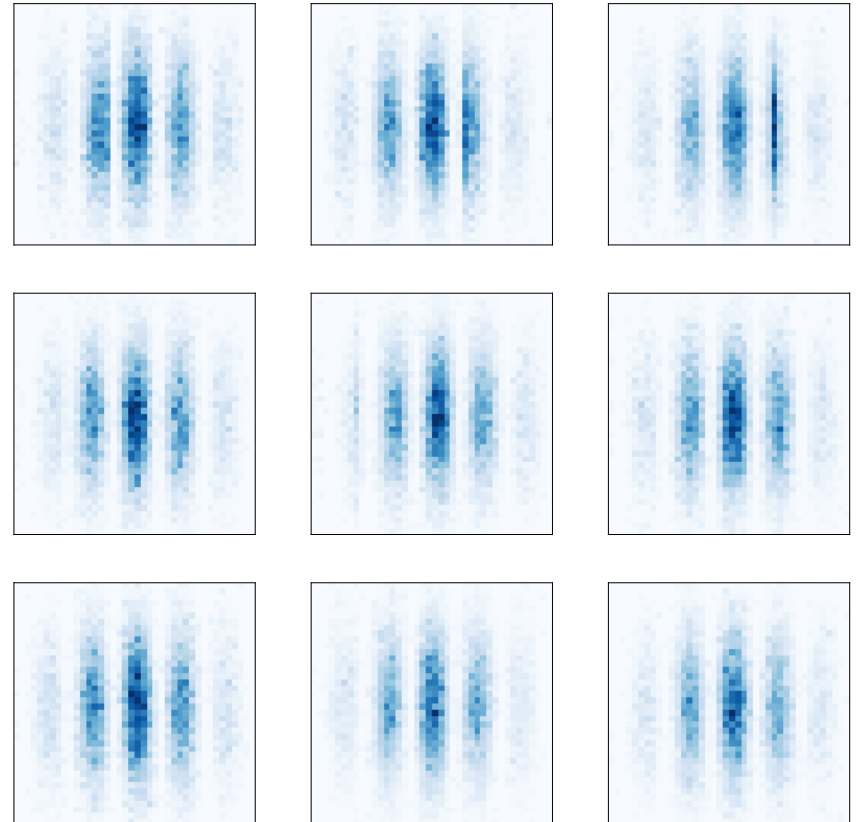


Patches of 40 x 40 pixels (500 mirrors)

Simulated views (2)

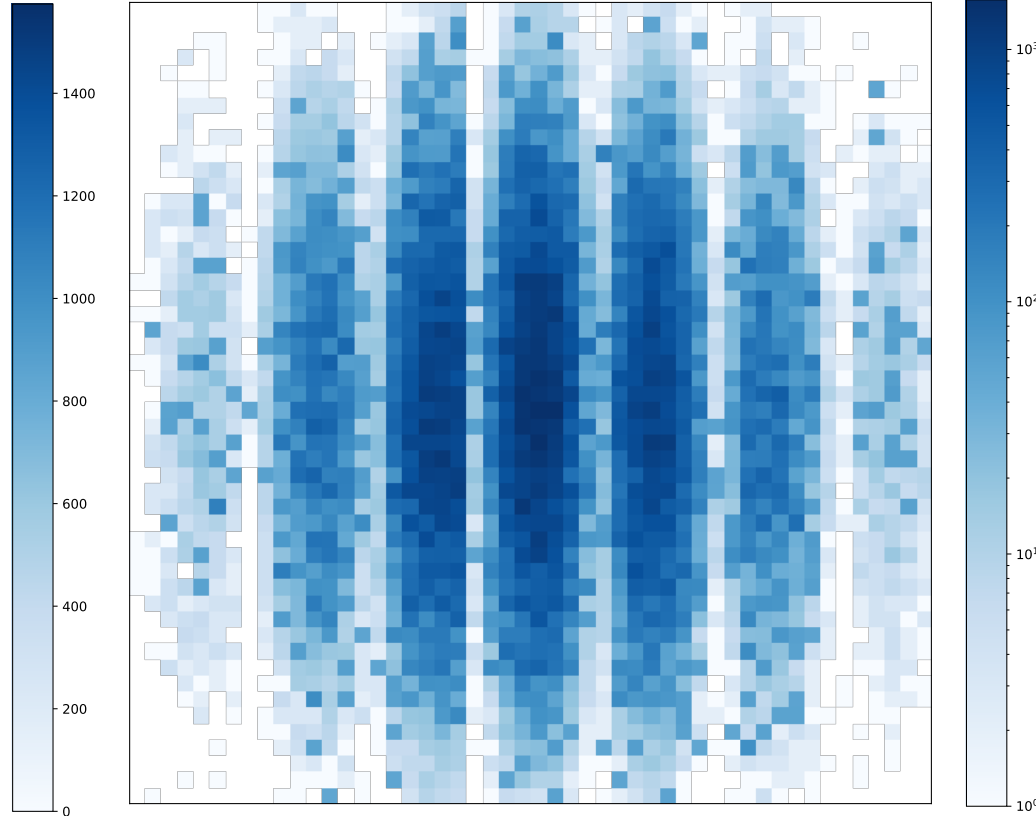


Views from the 100 mirrors (out of 500) that are the closest to the optical axis.



Views from the 9 mirrors that are the closest to the optical axis.

Simulated views (3)



View from the mirror that is the closest to the optical axis (50 x 50 pixels).

View from the mirror that is the closest to the optical axis (logarithmic norm).

- The simulator will be a key component in the inference pipeline.
- Enables **3d reconstruction & simulation-based inference** in order to learn confidence intervals or posterior distributions over ϕ or $\Delta\phi$.
- The simulator's differentiability allows solving $\|A(x) - b\|^2$ (or other reconstruction objectives) with gradient descent.
 - b is an observed image.
 - A is the differentiable simulator.
 - x is the model of the atom cloud.
 - E.g. parametrized wave function, voxel, neural network, implicit function, ...

- Photon mapping.
 - Rays are traced **from source to sensor** (current approach).
 - Requires to model the interaction of 1B rays with the system (computational expensive).
 - Makes it difficult to compute $\|A(x) - b\|^2$ and its gradients in a tractable manner.
- Path tracing:
 - Rays are traced **from sensor to source** (being implemented).
 - Integrate radiant flux over the ray's path.
 - Most common approach used in computer graphics.
 - Allows to query the value of a single pixel and do per-pixel minibatch gradient descent.

Next steps

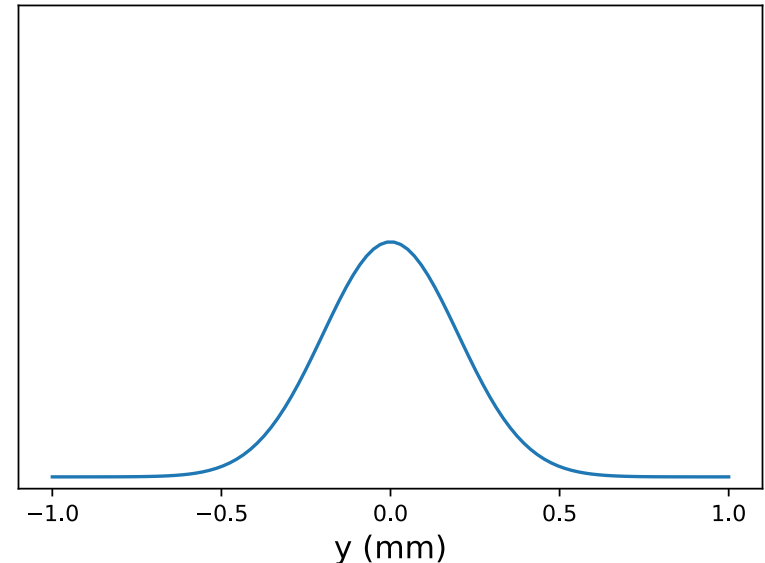
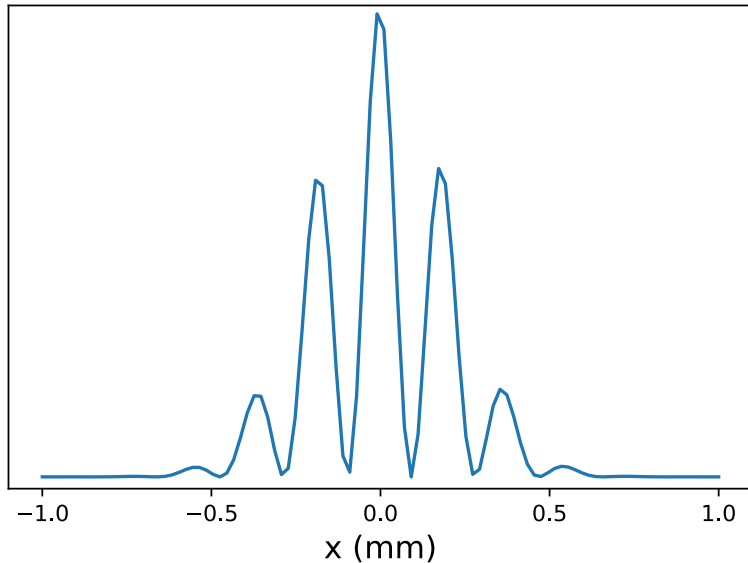
1. Finish the **path tracing** implementation.
2. First implementation of **3d reconstruction & maximum likelihood estimation** of parameters given a wave function from.
3. Add more sources of noise & complexity to make the simulator more realistic.
4. Interface the simulator with ML approaches to **simulation-based** inference.

Questions

- Does the interference pattern always face the same direction?
- Do we need to consider any coherence between emitted photons?
- Given the low number of photons, can we still model the photon paths with classical geometric optics?
- Should we target including lasers-induced noise sources in the near term?
- Are there existing simulators / resources for understanding how to simulate the wave function propagation through the pipe.

Interference pattern

$$\frac{i \left(\frac{2}{\pi}\right)^{3/4} (mw_0)^{3/2} \left(\frac{1}{\sqrt{2}} + \frac{e^{i(a_{\text{Quad}} k_{\text{Fringe}}^2 x^2 + k_{\text{Fringe}} x)} + i\phi}{\sqrt{2}} \right) e^{-\frac{m((x-x_A)^2 + (y-y_A)^2 + (z-z_A)^2)}{4mw_0^2 + 2i t_{\text{FinalBS}} \hbar}}}{\sqrt{-(2mw_0^2 + i t_{\text{FinalBS}} \hbar)^3}}$$



Gradients and 3d reconstruction

- The simulator's differentiability allows forwarding per-pixel gradients to the cloud parameters (chain rule).

