Phase Space Reconstruction of LCLS Beam Images using Machine Learning

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Introduction

Phase space distribution of a particle beam is vital for understanding beam dynamics and optimizing accelerator performance. We aim to reconstruct particle beam distributions in 4D phase space:

$$\rho(x, p_x, y, p_y)$$

Tomographic Methods

- We utilize quadrupole scans by varying the strengths of the focusing magnets and observe the beam distribution on a screen
- In quadrupole scans, we use the rms beamsize and fit the initial parameters to achieve the beam matrix and emittance measurements

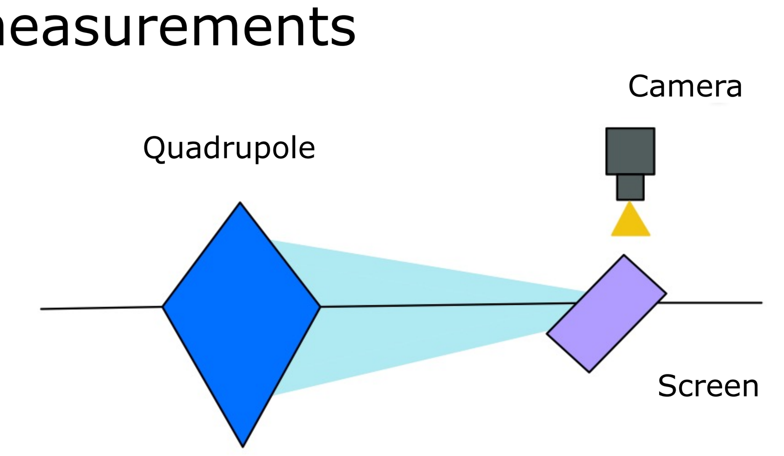

Figure 1: Simple quadrupole scan diagram where the beam distribution is projected onto a screen and an image of the transverse distribution is captured by the camera

- However, this method assumes a multivariate gaussian beam distribution and fails to capture a lot of information that we get from image diagnostics

Differentiable Simulations

To solve this problem, we combine two techniques to enable machine learning based reconstruction:

Neural network parameterization of beam distributions

- We collect samples from a gaussian distribution and transform the 6D particle coordinates with a NN into a final distribution to achieve a realistic distribution of phase space coordinates

Differentiable particle tracking through accelerator beamlines

- Implement particle tracking code Bmad such that it preserves differentiability in a ML library such as PyTorch
- This allows for taking derivatives of any parameter with respect to any other parameter

Experimentally, this allows for taking the derivative of pixel intensities with respect to initial coordinates and, by the chain rule, we can calculate intensities of pixels with respect to NN parameters. By minimizing the loss function, describing the difference between the images and using gradient descent to train the NN, we produce the reconstructed beam distribution at the start of the beamline.

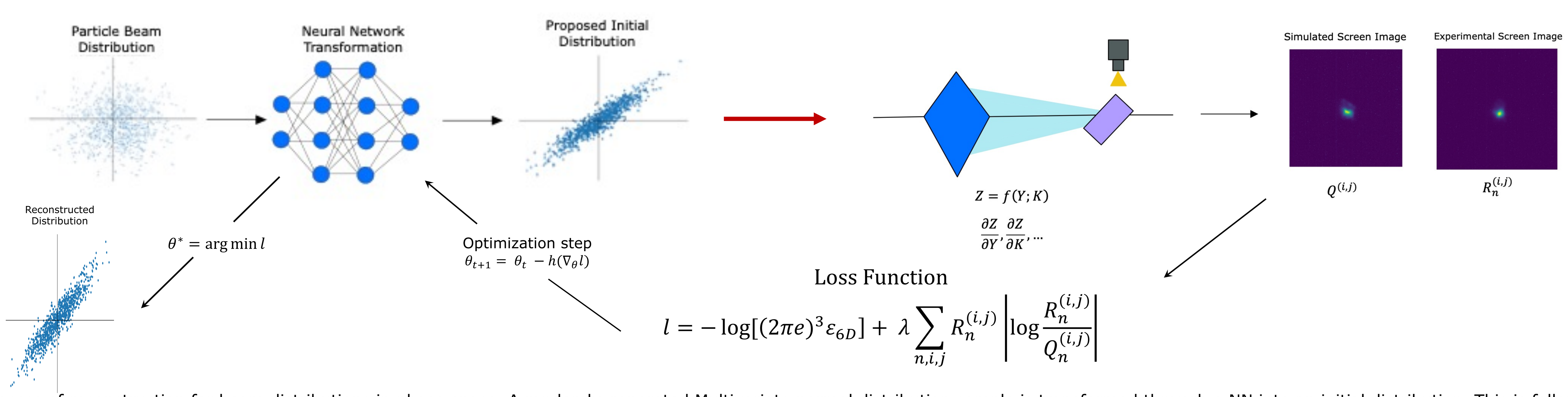

Figure 2: The process of reconstruction for beam distributions in phase space. A randomly generated Multivariate normal distribution sample is transformed through a NN into an initial distribution. This is followed by a quadrupole scan where the initial distribution (Y) is transformed through the beamline to give the final distribution (Z), where we are allowed to optimize our problem by taking derivatives with respect to both Y and the beam parameters (K). The difference of simulation and experimental images are minimized through a loss function, which then updates NN parameters, and produces the reconstructed initial beam distribution.

Results

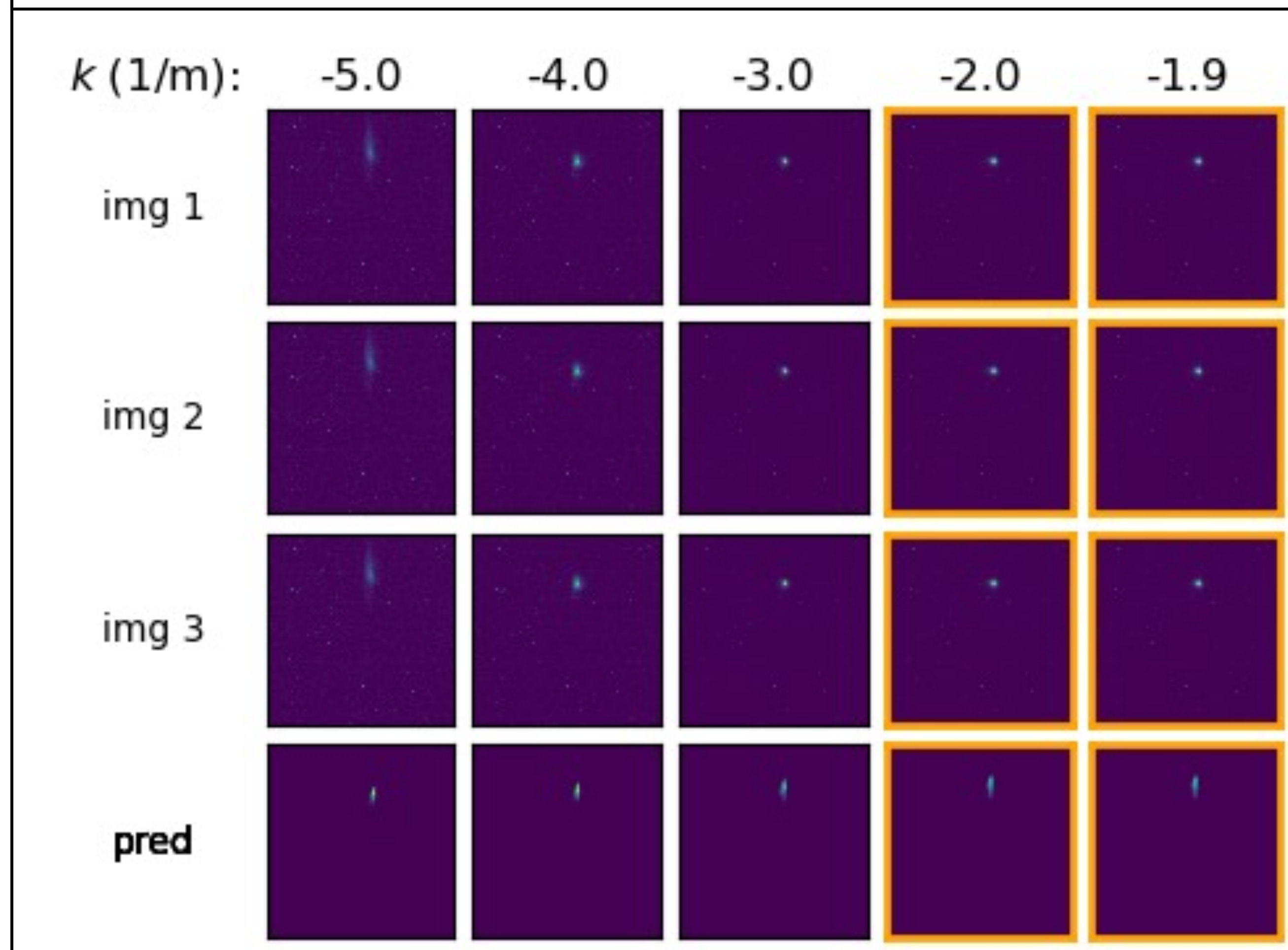

Figure 3: Beam images from 2021 LCLS experiment run with five quadrupole settings, each with three images per quadrupole strength. Test images (which were not shown to the algorithm) are boxed in orange. The predicted beam images are shown in the last row

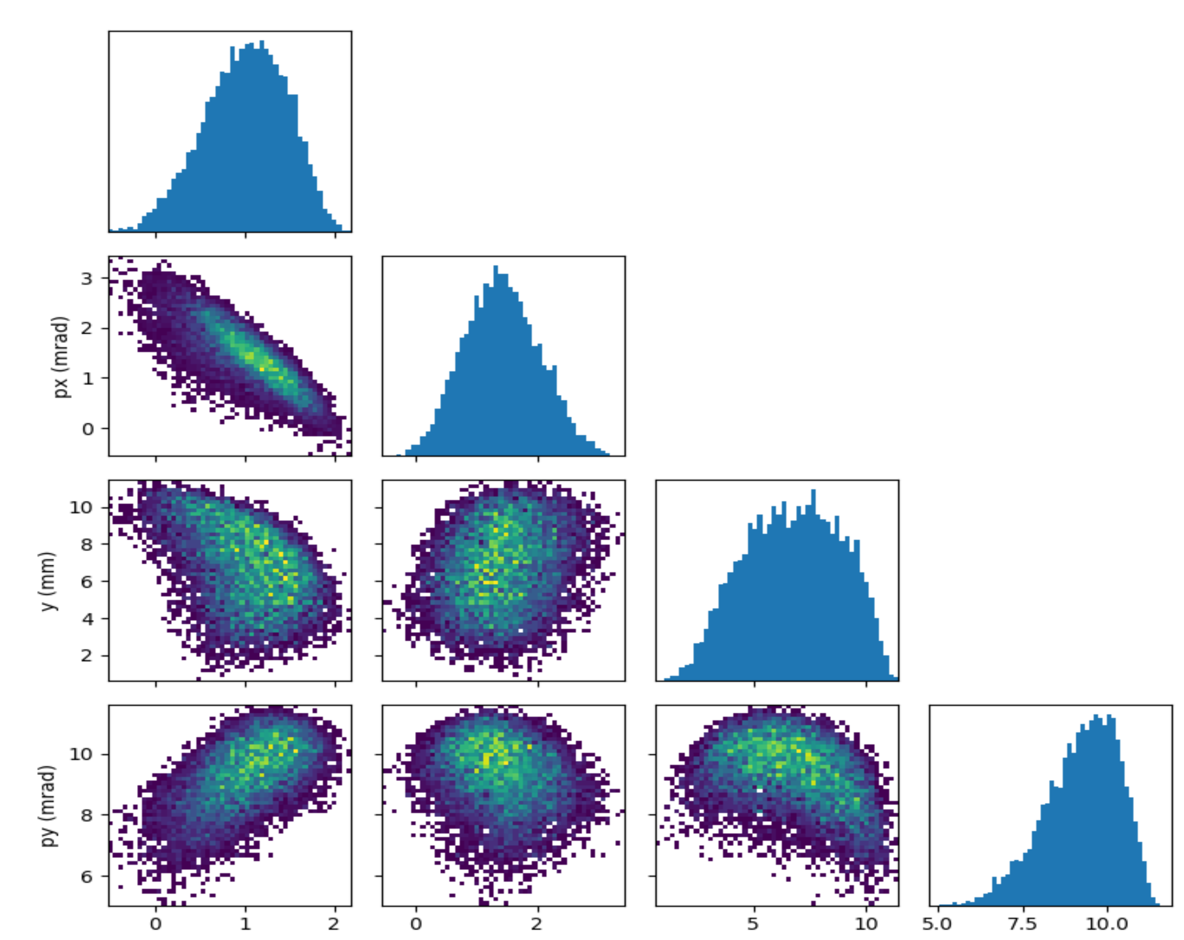

Figure 4: Plotted projections of the particle beam distribution in phase space in a 4D coordinate system

Conclusions

We can use tomography methods and neural networks in machine learning to accurately reproduce realistic features in particle beam distributions in 4D phase space

Next Steps

We want to reproduce results from 4D phase space in 6D phase space from just transverse beam images, as well as make differentiable simulations more accurate by accounting for space charge effects, wakefields, etc.

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