ISBN: 978-3-95450-219-6 ISSN: 2226-0366 doi: 10.18429/JACoW-LINAC2024-TUAA005

BEAM EMITTANCE AND TWISS PARAMETERS FROM PEPPER-POT IMAGES USING PHYSICALLY INFORMED NEURAL NETS*

I. J. Knight†, Georgia Institute of Technology, Atlanta, GA, USA
B. Mustapha, Argonne National Laboratory, Lemont, IL, USA

Abstract

In the field of accelerator physics, the quality of a particle beam is a multifaceted concept, encompassing characteristics like energy, current, profile, and pulse duration. Among these, the emittance and Twiss parameters—defining the size, shape, and orientation of the beam in phase space—serve as important indicators of beam quality. Prior studies have shown that carefully calibrated statistical methods can extract emittance and Twiss parameters from pepper-pot emittance meter images. Our research aimed to retrieve these parameters with machine learning (ML) from a transverse image of the beam after its propagation through a pepper-pot grid and subsequent contact with a scintillating plate. We applied a Convolutional Neural Network (CNN) to extract the x and y emittances and Twiss parameters (α and β), producing a six-dimensional output by simply looking at the image without calibration information. The extraction of divergence-dependent parameters, such as α and emittance, from a single image presented a challenge, resulting in a large Symmetric Mean Absolute Percentage Error (SMAPE) of 30%. To mitigate this issue, our novel method that incorporated image data from two points along the particles' propagation path yielded promising results. β prediction achieved a low SMAPE of 10.5%, while α and emittance predictions were realized with a 16.5% SMAPE and 13.3% SMAPE, respectively. Our findings suggest the potential for improvement in ML beam quality assessment through multi-point image data analysis.

BACKGROUND

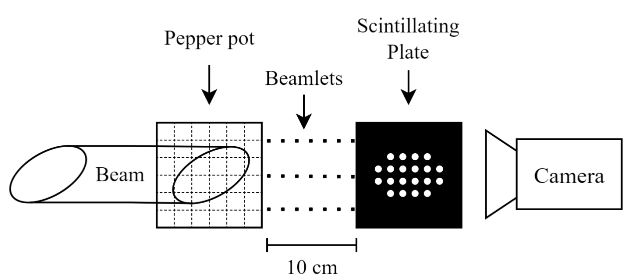

Figure 1: Pepper-pot emittance meter arrangement.

At the Argonne Tandem Linear Accelerator System (ATLAS), images of the beam are captured using a pepper-pot (PP) emittance probe. A pepper-pot is a plate with holes in it placed transverse to the beam splitting it into beamlets. In a PP emittance probe system, beamlets travel a short distance then hit a scintillating plate which fluoresces in those locations, see Fig. 1. An image of the plate is then captured by a camera, see Fig. 2.

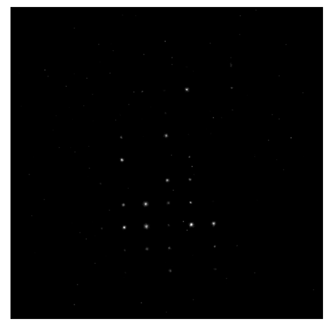

Figure 2: Real-world pepper pot image.

The beam envelope, the x and y extent of the beam, exist in physical space; phase space is a theoretical space defined by the momentum and physical positions of particles in the beam. Particles have position and momentum in three dimensions, for this reason there are 3 separate phase space ellipses in the absence of coupling. The longitudinal coordinate, z, is the direction the beam travels, and the (x, y) plane or transverse plane contains the image that PP metering captures.

$$\gamma x^2 + 2\alpha x x' + \beta x'^2 = \epsilon \tag{1}$$

where x' and y' represent momentum.

$$\frac{1+\alpha}{\beta} = \gamma \tag{2}$$

The distribution of momenta and position of particles when projected onto a phase plane generate an ellipse, referred to as the phase space ellipse. Twiss parameters (α, β, γ) and emittances (ϵ) define the size, shape, and orientation of the phase space ellipses as in Eq. (1). Beta is proportional to the extent of the beam, horizontal or vertical, in physical space. Emittance is the area of the phase space ellipse, and in physical space, it relates to the spread of the beam. Alpha is the correlation of position and momentum. Visually, it describes the tilt of the beam in phase space.

Problem Definition

Our PP images, defined in physical space, do not fully capture information about particles' momenta as they show a snapshot in time while momentum describes a process that changes over time. To extract the Twiss parameters from

* This work was supported by the U.S. Department of Energy, under Contract No. DE-AC02-06CH11357. This research used the ATLAS facility, which is a DOE Office of Nuclear Physics User Facility.
† ianknight@gatech.edu

ISBN: 978-3-95450-219-6 ISSN: 2226-0366 doi: 10.18429/JACoW-LINAC2024-TUAA005

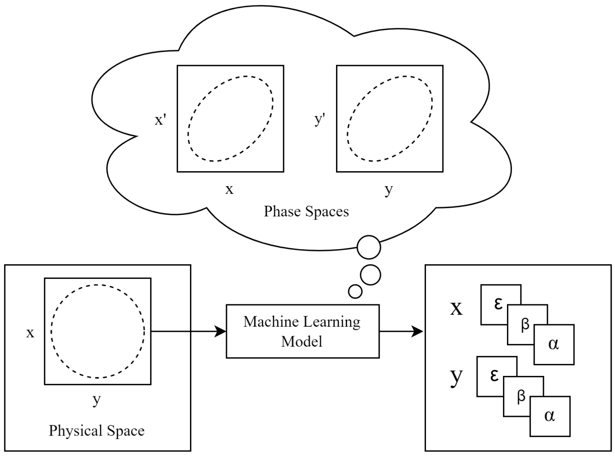

Figure 3: Machine learning system diagram.

an image in physical space, a model must somehow extract information about the particles' momentum. In statistical methods, this is done by calculating the change between the location of the beamlet when passing through the PP and contacting the scintillating plate, using known distances between the holes in the PP and the distance between the PP and plate to find the parameters [1, 2]. The goal of this work is to input a PP image and produce a 6D output containing the x and y Twiss parameters and emittance without including that additional information, see Fig. 3.

METHODS

Generating a large dataset of PP images for a exploratory study would be prohibitively expensive, therefore, this study uses the TRACKv39 beam dynamics software to generate a distribution of five million particles for the computation of each image [3]. The PP arrangement is simulated in Python. ϵ, α, and β were varied in the x and y dimensions with z being the direction of propagation[1]. The initial distributions of particles were generated with parameters in the ranges: α_x: [-5.0, 5.0], β_x: [50.0, 500.0], ϵ_x: [0.03, 0.30], α_y: [-5.0, 5.0], β_y: [50.0, 500.0], ϵ_y: [0.03, 0.30]; the target of prediction was the final beam distributions after drift. Collecting a large dataset (8,000+ 6-parameter varied examples) required scaled compute, TRACKv39 simulations were automated and parallelized in a computing cluster.

Measures of Prediction Error

$$\mathrm{SMAPE} = \frac{200}{n} \sum_{i=1}^{n} \frac{|y_i - \hat{y}_i|}{|y_i| + |\hat{y}_i|} \tag{3}$$

Models in this work were trained using Mean Squared Error (MSE), a standard in ML. Their performance statistics are stated with Mean Absolute Error (MAE) for interpretability and Symmetric Mean Absolute Error (SMAPE) when the relative accuracy of parameters is important. There are several common definitions of SMAPE, and Eq. (3) shows the formula used in this work.

[1] γ is excluded as it is dependant on α and β as in Eq. (2).

Physically Informed Neural Nets

This work leverages PINNs by adding observational bias to ML models in the form of data augmentation. Other principles of physics-informed learning, such as inductive biases through architectural interventions and learning biases via modified loss functions, were applied in this work but did not yield successful outcomes [4].

The benefit of applying ML to the analysis of PP images is two-fold. First, data-driven learning methods have the potential to continuously improve in accuracy as they are exposed to more data, unlike rule-based methods which remain static regardless of data scale. Second, ML enables the discovery of latent features within the data. In particular, our CNN method does not require direct information about the distance from the PP to the scintillating plate as this information is implicitly learned from the data. This implicit feature is now an expectation of the model, and there is no guarantee it will generalize to other distances.

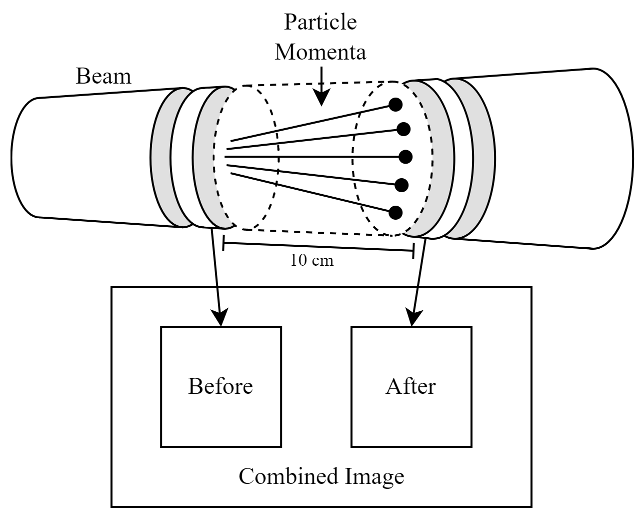

Figure 4: Example simulated before-after image.

After simulated propagation through the pepper-pot, particles are typically propagated a distance to inform a model of the particles' momenta. We propose that beam divergence or convergence, the change of momentum over distance, can be captured in a single input image by showing the before-and-after of a short propagation, see Fig. 4. This before-after image contains PP images from two points in propagation, e. g., Fig. 5. In simulated settings where movement of individual particles is known, generating images from a later point in propagation is simple. However, in a real beamline, this method requires the installation of a second PP system, which is prohibitive.

Model Descriptions

To gauge the ability of ML models to extract Twiss parameters and emittance from PP images a Convolutional Neural Network (CNN), a Multi-Layer Perceptron (MLP), and a Ridge Regression (RR) model were fit to the simulated dataset. SciPy's RR and a range of standard MLPs, subject

ISBN: 978-3-95450-219-6 ISSN: 2226-0366 doi: 10.18429/JACoW-LINAC2024-TUAA005

Figure 5: Example simulated before-after image.

to architecture search, were used. Images were flattened for both the MLP and RR. An AlexNet-like CNN structure was used [5].

RESULTS

To decide the propagation distance hyperparameter we varied it and found 0 cm and 10 cm pairings were the most performant outperforming single images by 21.20% MAE in Ridge regression on a test set, averaged across all parameters (p = 0.03).

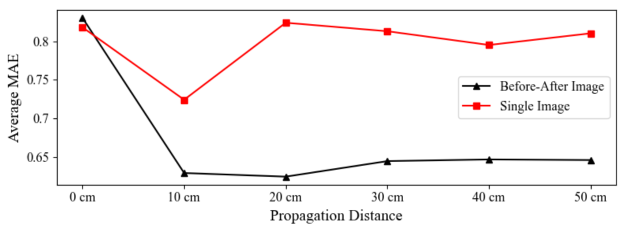

Figure 6: Ridge regression MAE by propagation distance.

Depicted in Fig. 6, we varied the propagation distance and found that increasing propagation distance does not improve model performance. Single images also benefit from propagation. Training with single images that have an additional propagation after the PP results in lower error. Immediately after the PP, difference in beamlet size is not obvious. Visual inspection after a short propagation shows differences in beamlet size across the image, revealing divergence or convergence in the beam.

Machine Learning

All numbers reflect ensemble models subject to Bayesian hyperparameter sweeps trained on the entire 8,755 image dataset split into 70% train, 10% validation, and 20% test. The performance on a common test set[2] is reported from the best run on the validation set (see Table 1 and Table 2).

Table 1: SMAPE for Single Images

Model	ϵ_x	α_X	β_x	ϵ_Y	α_Y	β_Y
MLP	44.1	96.0	90.2	43.5	97.4	90.8
Ridge R.	21.1	67.8	60.2	20.2	67.6	60.9
CNN	20.0	39.4	24.7	22.4	37.5	17.8
Ensemble	20.0	39.4	24.7	20.2	37.5	17.8

[2] Defined as a random selection of parameters.

Table 2: SMAPE for Before-After Images

Model	ϵ_x	α_X	β_x	ϵ_Y	α_Y	β_Y
MLP	44.1	80.6	75.6	42.0	81.0	74.5
Ridge R.	18.2	63.7	52.2	17.9	61.8	53.6
CNN	19.0	16.0	12.0	14.9	10.6	9.0
Ensemble	18.2	16.0	12.0	14.9	10.6	9.0

CONCLUSIONS

Although PP emittance metering has been shown to be a reliable method of extracting emittance and Twiss parameters from transverse beam images, a simple learning method does not suffice to capture the relationship between the parameters and image. Giving further information to the model in the form of data augmentation or model structure is required to push beyond a threshold of performance for momentum-dependant beam parameters.

Further work is needed to validate learning methods on images from a live accelerator. To test the performance ML models with a statistical method developed for real images, like in Barabin et. al., a simulation must generate images that are indistinguishable from real images or work must be done to transfer their method to simulated data. Additionally, further work is needed in adding inductive and learning biases to PINNs in PP analysis as only data augmentation has so far yielded results.

ACKNOWLEDGEMENTS

This work was conducted in the course of the 2023 Lee Teng Fellowship at the Argonne Physics Division.

REFERENCES

[1] A. Kondrashev *et al.*, "Development of a Pepper Pot Emittance Probe and Its Application for ECR Ion Beam Studies", *Nucl. Instrum. Methods Phys. Res. Sec. A*, vol. 3, pp. 296–304, 2009. doi:10.1016/j.nima.2009.04.050

[2] S. Barabin *et al.*, "Pepper-Pot Emittance Measurements", in *Proc. RuPAC'18*, Protvino, Russia, Oct. 2018, pp. 443–445. doi:10.18429/JACoW-RUPAC2018-THPSC18

[3] TRACK: The Beam Dynamics Code, Argonne National Laboratory, Accessed: Aug. 19, 2024. https://www.phy.anl.gov/atlas/TRACK/

[4] G. E. Karniadakis, I. G. Kevrekidis, L. Lu, P. Perdikaris, S. Wang, and L. Yang, "Physics-Informed Machine Learning", *Nat. Rev. Phys.*, vol. 3, no. 6, pp. 422–440, 2021. doi:10.1038/s42254-021-00314-5.

[5] A. Krizhevsky, I. Sutskever, and G. E. Hinton, "ImageNet Classification with Deep Convolutional Neural Networks", *Adv. Neural Inf. Process. Syst.*, vol. 25, pp. 1097 - 1105, 2012. https://proceedings.neurips.cc/paper_files/paper/2012/file/c399862d3b9d6b76c8436e924a68c45b-Paper.pdf