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6D PHASE SPACE DIAGNOSTICS BASED ON ADAPTIVELY TUNED PHYSICS-INFORMED GENERATIVE CONVOLUTIONAL NEURAL NETWORKS

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Abstract

A physics-informed generative convolutional neural network (CNN)-based 6D phase space diagnostic is presented which generates all 15 unique 2D projections (x, y), (x, y'),...,(z, E) of a charged particle beam's 6D phase space (x, y, z, x', y', E). The CNN is trained by supervised learning over a wide range of input beam distributions, accelerator parameters, and the associated 6D beam phase spaces at multiple accelerator locations. The CNN is applied in an unsupervised adaptive manner without knowledge of the input beam distribution or accelerator parameters and is robust to their unknown time variation. Adaptive feedback automatically tunes the low-dimensional latent space of the encoder-decoder CNN to predict the 6D phase space based only on 2D (z, E) longitudinal phase space measurements from a device such as a transverse deflecting RF cavity (TCAV). This method has the potential to provide diagnostics beyond the existing state of the art at many accelerator facilities. Studies are presented for two very different accelerators: the 5-meter-long ultra-fast electron diffraction (UED) HiRES compact accelerator at LBNL and the kilometer long plasma wakefield accelerator FACET-II at SLAC.

INTRODUCTION

Particle accelerators are large complex systems with many coupled components. Accelerator beams are complex objects with dynamics governed by nonlinear collective effects such as space charge and coherent synchrotron radiation. Because of their complexity, particle accelerator controls and diagnostics can greatly benefit from advanced machine learning (ML) [1], and control theory techniques.

Supervised learning techniques are being applied at CERN for the reconstruction of magnet errors in the incredibly large (thousands of magnets) LHC lattice [2]. Bayesian methods have been developed for online accelerator tuning of the LCLS [3], Bayesian methods with safety constraints are being developed at the SwissFEL and the High-Intensity Proton Accelerator at PSI [4], and at SLAC Bayesian methods are being developed for the challenging problem of hysteresis [5] and surrogate models are being developed for the beam at the injector [6]. Convolutional neural networks (CNN) have been used to generate incredibly high resolution virtual diagnostics of the longitudinal phase space (LPS) of the electron beam in the EuXFEL [7]. A laser plasma wakefield accelerator has also been optimized by utilizing Gaussian processes at the Central Laser Facility [8].

A limitation of standard ML methods is the requirement of re-training whenever a system changes. Because accelerators are changing continuously and detailed beam measurements usually interrupt operations repetitive re-training is not a feasible solution. Recently, powerful model-independent feedback control methods, known as extremum seeking (ES), have been developed which can handle unknown and quickly time-varying nonlinear systems in which the direction of the controller's input is unknown and quickly time-varying [9, 10]. For example, it is possible to use ES for RF cavity resonance control based only on ambiguous reflected power measurements [11]. A limitation of model-independent feedback is the possibility of getting stuck in a local minimum.

Due to the complimentary strengths and weaknesses of ML and model-independent feedback, efforts are being made to combine the two fields via adaptive ML (AML) which provides the best of both worlds: an ability to learn directly from large complex data, while maintaining robustness to time variation and distribution shift. The first demonstration of the AML approach was the use of neural networks together with ES for automatic control of the time-varying longitudinal phase space distribution of the LCLS beam [12]. AML methods have also combined CNNs and ES to track time-varying input beam distributions at the HiRES UED [13], and preliminary results have shown an ability to adaptively tune the low-dimensional latent space of encoder-decoder CNNs to track all 15 unique 2D projections of beam's 6D phase space despite unknown and time-varying input beam distributions and accelerator and beam parametes [14].

AML FOR 6D DIAGNOSTICS

In this work we present simulation-based AML studies at the HiRES UED [15], for predicting all 15 unique 2D projections of a charged particle beam with unknown and time-varying input beam conditions at the photocathode, unknown beam charge and injector solenoid magnet strength, and demonstrate that this method has the capability to accurately predict beyond the span of the training set data.

Time-varying systems, or systems with distribution shift, are an open problem and an active area of research in the ML community [16–20]. In this work we tackle the problem of distribution shift by incorporating model-independent adaptive feedback directly within the architecture of an encoder-decoder CNN which takes beam distributions and parameters (charge and solenoid current) as inputs and generates

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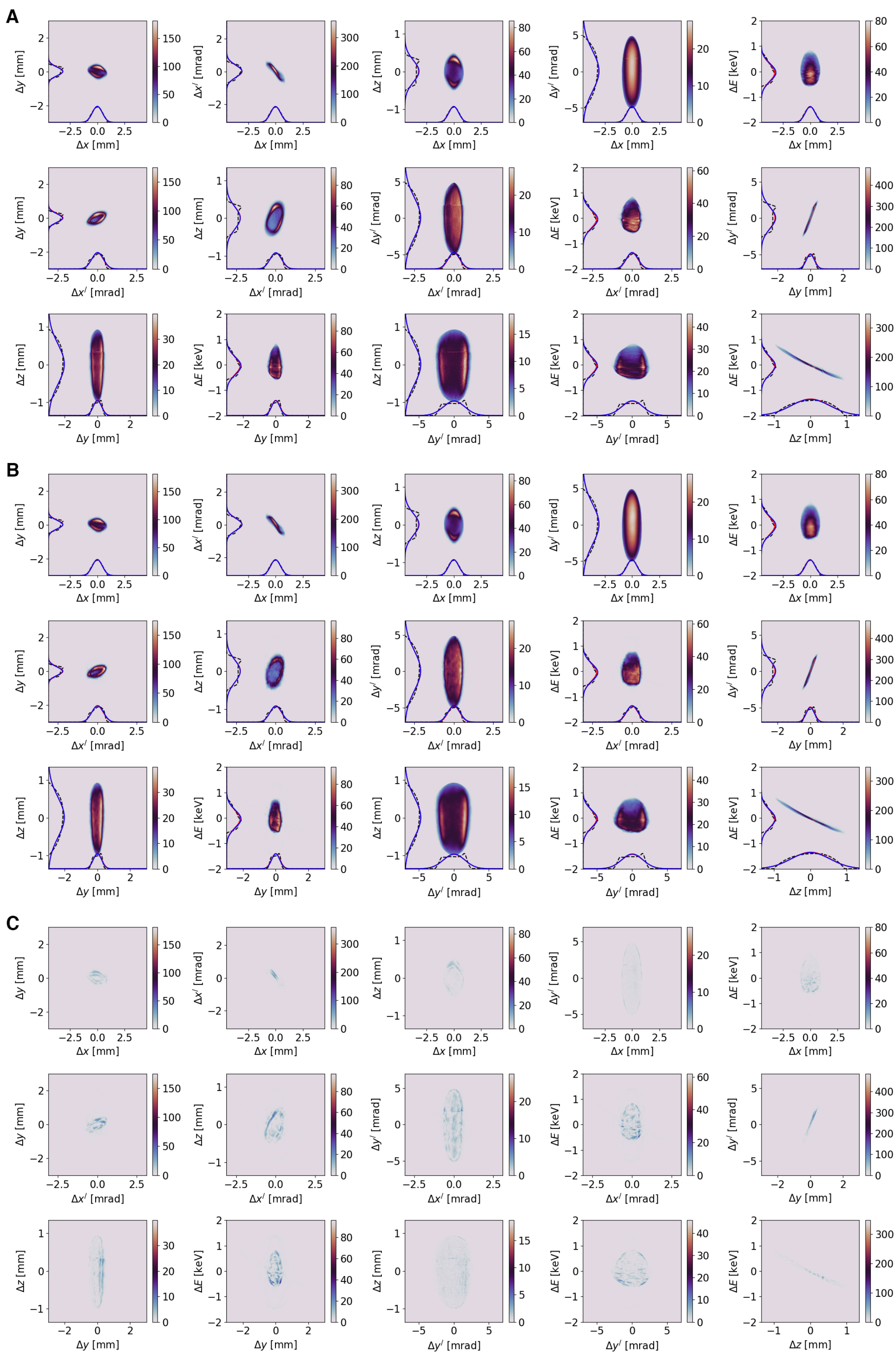

Figure 1: **A:** 15 2D projections of a beam's 6D phase space, ρ_{ij}. **B:** The same 15 2D projections generated by the CNN, $\hat{\rho}_{ij}$. **C:** Absolute difference $|\hat{\rho}_{ij} - \rho_{ij}|$. Color scale of each projection set by maximum value of actual projection: $\max\{\rho_{ij}\}$.

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15 256×256 pixel 2D projections (~ 10^6 dimensions) of the beam's 6D phase space downstream from the injector, as shown in Fig. 1, where the CNN's predictions are compared to the ground truth for a beam with unknown input distribution and unknown charge passing through an accelerator with an unknown solenoid strength. Our CNN is applied in an unsupervised adaptive way by squeezing down to a 2D latent space between the encoder and decoder sections which is adaptively tuned using ES with time-varying cost

$$C(t) = \iint \left|\rho_{z,E}(t) - \hat{\rho}_{z,E}(t)\right| dEdz, \qquad (1)$$

a comparison between the CNN's longitudinal phase space (LPS) prediction $\hat{\rho}_{z,E}$ and the measurement of the LPS as provided by a TCAV $\rho_{z,E}$. By forcing the CNN to simultaneously generate all 15 projections of the 6D phase space we introduced observational biases directly through data embodying the underlying physics, allowing the CNN to learn functions that reflect the physical structure of the data [21].

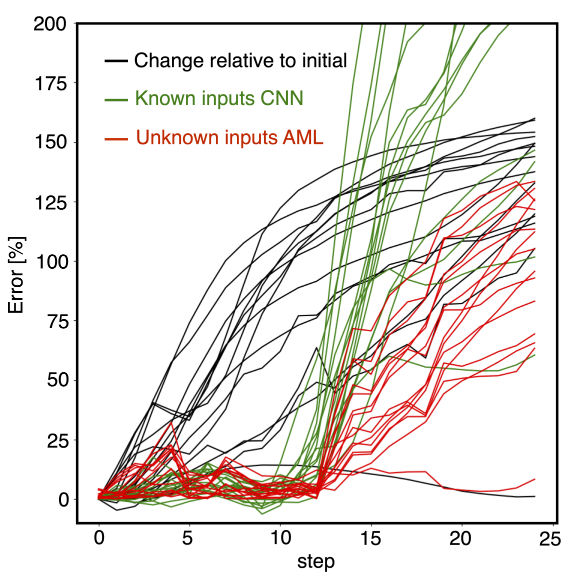

Figure 2: Error is shown in percent for each of the 15 projections of the beam's 6D phase space as the input beam distribution, charge, and solenoid strength are moved beyond the span of the training set.

TRACKING PHASE SPACE

Figure 2 shows the results of changing the input beam distribution, beam charge, and solenoid current far beyond the span of the training data. The black lines show the change relative to the initial starting condition. The green lines show the CNN's errors if assuming known beam distribution, charge, and solenoid strength, with catastrophic failure beyond the span of the training set where the CNN's predictions are far worse than simply doing nothing. Finally, the red lines show the error when we do not have access to the unknown beam distribution, charge, and solenoid strength, but with the use of adaptive feedback which has access to the (z, E) projection to be used as feedback within the latent space by continuously minimizing the cost function (1).

CONCLUSIONS

We have demonstrated preliminary studies of a physics-informed AML method for tracking all 15 projections of a charged particle beam with unknown and time-varying initial distribution and charge at the photocathode and unknwon and time-varying solenoid strength at the injector based only on TCAV measurements of the (z, E) LPS.

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