TRANSVERSE PHASE SPACE TOMOGRAPHY AT CLARA USING GENERATIVE MACHINE LEARNING

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Abstract

CLARA is a high-brightness electron beam facility at STFC Daresbury Laboratory, aiming to deliver ultra-short electron bunches to a wide range of user experiments. CLARA has recently resumed operations after a major upgrade, and is currently undergoing beam commissioning at its nominal energy (250 MeV) and bunch charge (250 pC). During commissioning, studies of the transverse beam dynamics will be vital for optimizing the accelerator's performance, and for validating the simulation models used during its design. Phase space tomography is a powerful technique for reconstructing a beam's charge distribution in phase space; recent machine learning advances have led to faster, higher-resolution tomographic methods such as generative phase space reconstruction. In this contribution, we present detailed measurements of the 4D transverse phase space at CLARA. We validate the reconstructed phase spaces by using them to accurately predict the appearance of the electron beam for different beam optics configurations. Our results demonstrate methods that are now used for routine characterization of the CLARA beam, and represent the first emittance measurements at the accelerator's design energy.

INTRODUCTION

CLARA at STFC Daresbury Laboratory is a medium energy (250 MeV) linear accelerator that delivers high-brightness, ultra-short electron bunches to a variety of demanding user experiments [1,2]. CLARA is currently undergoing beam commissioning at its maximum bunch charge (250 pC) and repetition rate (100 Hz), after an extended shutdown to allow the installation of a major upgrade. This period saw the addition of a new, high-repetition-rate (up to 400 Hz) electron gun [3]; three additional S-band accelerating linacs; a variable bunch compressor; and an X-band linearizer [4]. During commissioning, detailed measurements of the beam dynamics are essential to optimizing the beam properties ready for user experiments.

Phase space tomography [5–7] is a established method for reconstructing a beam's charge distribution in two or more degrees of freedom. Tomography in two transverse degrees of freedom provides detailed insights into the beam's substructure, and also allows measurement of the betatron coupling. Conventionally, tomography in multiple degrees of freedom has required large data sets and significant computational resources, making it unsuitable for online beam measurements. However, several authors have recently demonstrated new tomographic methods that use machine learning (ML) to quickly reconstruct a beam's charge distribution in unprecedented detail [8, 9]. Experimental studies have shown how these techniques can efficiently reconstruct a beam's full six-dimensional charge distribution, including its time structure and energy spectrum [10, 11].

One aim of CLARA commissioning is to characterize, and ultimately improve, the transverse distribution of the electron beam. Phase space tomography is well-suited to this application, since it can reconstruct an accurate charge distribution that includes the beam's detailed substructure. Previous tomography studies at CLARA [8, 12, 13] have reconstructed the low-energy (35 MeV) beam produced by the accelerator's front end, which was previously operated as a separate user facility between 2018–2022 [14]. However, updated tools have now been developed to characterize the CLARA beam at its design energy of 250 MeV.

These proceedings describe experimental studies aimed at reconstructing the transverse phase space of the high-energy CLARA beam. We use an ML-based method [9, 15] to infer the beam's charge distribution, before using it to accurately predict the beam profile for different quadrupole settings. The method demonstrated here is currently used for routine characterization of the CLARA electron beam, and has already been used in support of several user experiments.

METHOD

Experimental Data

Figure 1 shows the section of CLARA that was used for tomography measurements in this study. The transport and diagnostics section immediately after the final linac includes ten independently-powered quadrupole magnets, and four YAG screens for observing the beam profile. When energized, the first dipole magnet diverts the beam along a spectrometer line, which can be used to measure the beam energy. The second dipole in Fig. 1 directs the beam into a 16-meter-long arc, which delivers electron bunches to the full energy beam exploitation (FEBE) area. The FEBE area is a separately shielded enclosure that includes two large, configurable chambers where the majority of CLARA user experiments take place [16].

Here, we demonstrate the tomography methods used at CLARA by reconstructing the charge distribution of the 250 MeV electron beam for bunch charges up to 250 pC. For the purposes of this study, we made measurements of an

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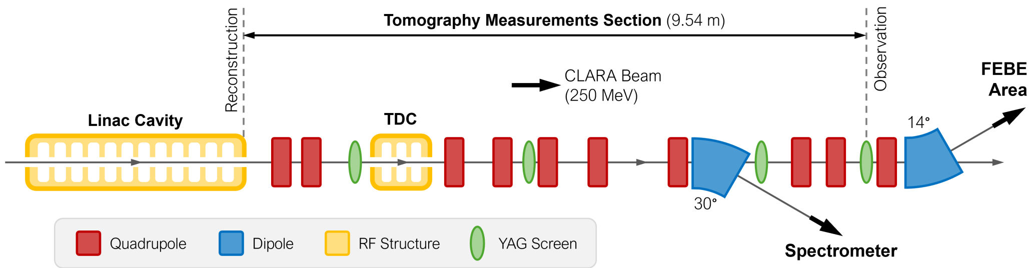

Figure 1: Simplified schematic showing the section of CLARA that was used for tomography measurements. The distances between elements are approximately to scale. Components that are not relevant to this study are not shown for clarity.

uncompressed beam, with the linac phases set to minimize the beam energy spread. We aimed to reconstruct the beam's transverse (x, p_x, y, p_y) phase space at the linac exit (the reconstruction point; see Fig. 1), using images from a YAG screen at the end of the straight (the observation point).

Before collecting tomography data, a simple, single-magnet quadrupole scan was used to estimated the Twiss (Courant-Snyder) parameters at the reconstruction point. Based on this measurement, an ELEGANT [17] model of the accelerator lattice was used to find 32 different quadrupole settings, which give a range of phase advances between the reconstruction and observation points. Figure 2 shows the horizontal and vertical phase advance for each step of the quadrupole scan that was used to collect tomography data. Quadrupole settings were chosen to keep the Twiss beta functions at the observation point approximately constant, avoiding beams with very small or large aspect ratios.

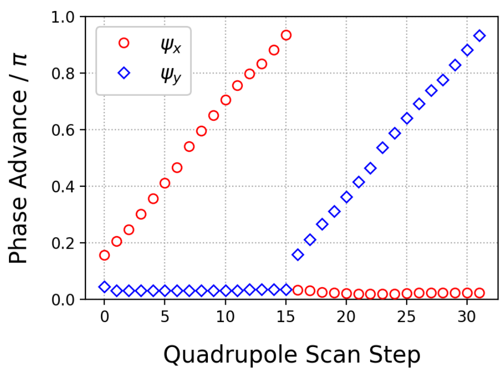

Figure 2: Betatron phase advance between the reconstruction and observation points (see Fig. 1), for each step of the quadrupole scan that was used to collect tomography data.

Before analysis, a background frame (taken with the photoinjector laser shutter closed) was subtracted from each beam image to remove contributions from dark current. Each image was then cropped to a fixed size of 300 x 300 pixels (approximately 3.8 mm per side) to maximize the area occupied by the beam.

Data Analysis

For this study, we used the generative phase space reconstruction (GPSR) technique to reconstruct the transverse phase space of the CLARA beam from a series of experimental beam images. The GPSR approach has already been described in detail elsewhere [9–11, 15]; however, a brief summary is included here for completeness.

The GPSR method is built around an artificial neural network ('the generative model'), which is used to generate macroparticle distributions at the reconstruction point. The generative model transforms random samples, drawn from an arbitrary probability distribution, into macroparticle coordinates for one or more degrees of freedom. Particle distributions generated by the model can be propagated through a representation of the accelerator lattice to produce simulated beam images at the observation point.

To generate a particle distribution that is consistent with experimentally measured beam images, the generative model must be trained. This is done by repeatedly using the model to generate new macroparticle distributions, while optimizing its parameters to minimize the difference between the measured beam images and an equivalent set of images simulated from the generated distribution. Due to the large number of free parameters in any neural network, conventional optimization algorithms are generally ineffective. Instead, the model must be trained using a more powerful, gradient-based optimization method such as ADAM [18]. The computational cost of using gradient-based optimization can be greatly reduced by using a differentiable linear optics code [19] to produce the simulated beam images.

For this study, we implemented a version of the GPSR method in `python`, using the PyTorch ML library [20]. The generative model was implemented as a simple neural network, with a single hidden layer comprised of 15 neurons connected by Tanh activation functions. We calculated the simulated beam images using Cheetah [21, 22], a fast, differentiable linear optics code that is specifically designed for ML applications. Each model was trained for 3000 iterations, generating 10^5 macroparticles from each proposed distribution to calculate the simulated images.

Training a new model typically takes 15 minutes on a NVIDIA 3090 RTX GPU. This is comparable to the time required for previous tomography analyses using conventional techniques [8]. However, the GPSR method generally produces a far more detailed representation of the beam's phase space.

RESULTS

The tomography method described in the previous section was applied to measurements of the 250 MeV CLARA beam,

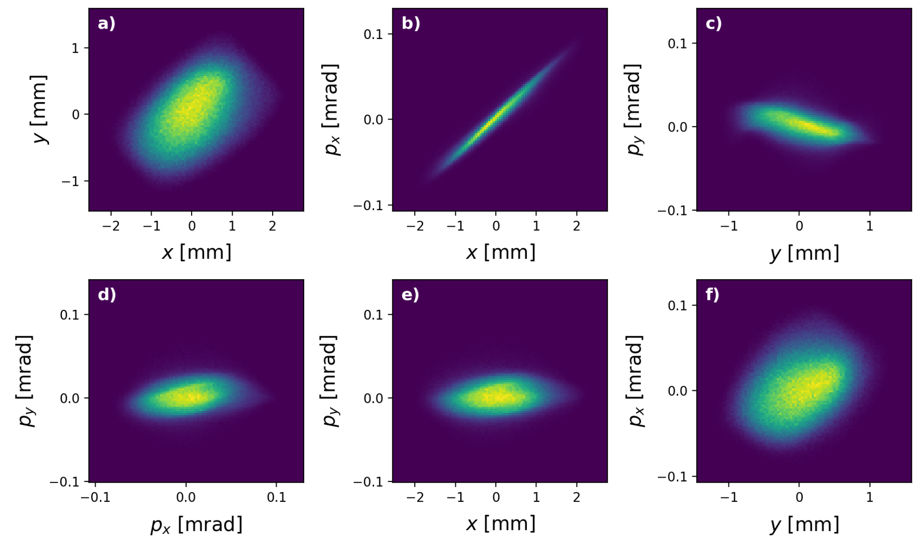

Figure 3: Projections of the CLARA beam's transverse (x, p_x, y, p_y) phase space at the reconstruction point, for a 250 MeV electron beam with a bunch charge of 30 pC.

Table 1: Reconstructed RMS Emittances for the 250 MeV CLARA Electron Beam for Bunch Charges up to 250 pC

Parameter	30 pC	100 pC	250 pC
$\epsilon_{n,x}$ [µm]	1.2	1.8	2.3
$\epsilon_{n,y}$ [µm]	1.6	2.1	2.2

for various bunch charges up to 250 pC. Figure 3 shows the projections of the beam's 4D transverse phase space, reconstructed after the final linac for a bunch charge of 30 pC. Our measurements produce high-fidelity images of the phase space projections, showing the beam's detailed substructure even at a reduced bunch charge.

Table 1 lists the normalized emittance that was obtained from the covariance matrix of the reconstructed phase space at each bunch charge. We note that these values were measured during commissioning of the accelerator, and do not reflect its expected performance when fully operational.

The reconstructed phase spaces can be validated by using them to predict the beam profile at the observation point for different quadrupole settings. Figure 4 shows comparisons between three measured and reconstructed beam profiles, each corresponding to a different bunch charge. Qualitatively, there is good agreement between pairs of images, in terms of both the beam's size and substructure.

CONCLUSIONS

The work reported in this contribution has demonstrated the use of generative ML to reconstruct the charge distribution of the CLARA electron beam at its maximum energy (250 MeV) and for bunch charges of 30, 100 and 250 pC. The method described here is currently used for routine characterization of the CLARA electron beam during commissioning. It has already been deployed to support several user experiments, providing an accurate representation of the beam's phase space distribution that is often needed for analysis of the experimental data.

Notably, the section of CLARA shown in Fig. 1 includes both a transverse deflecting cavity (TDC) and a spectrometer dipole. In future, we plan to use these components to reconstruct the beam's full, six-dimensional charge distribution, including information about its longitudinal phase space [9,10]. These measurements will be invaluable for user experiments that require highly compressed (<100 fs) electron bunches, including tests of novel acceleration schemes.

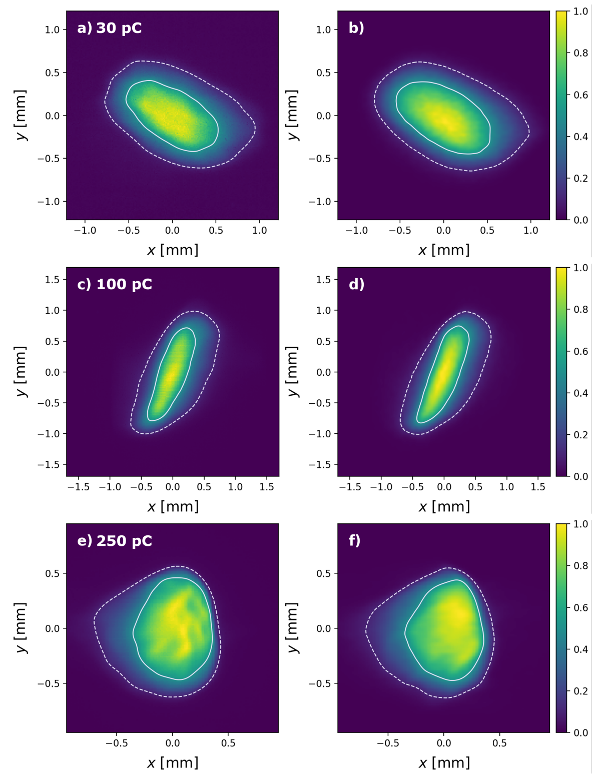

Figure 4: Examples of measured (left) and reconstructed (right) beam profiles at the observation point, for different bunch charges and quadrupole settings. The solid (dashed) contour denotes 50% (10%) of the maximum beam intensity.

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