FEL POWER PROFILE PREDICTIONS WITH IMAGE-BASED MACHINE LEARNING AT FLASH

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Abstract

Accelerator operators and beamline users can highly benefit from accurate and efficient measurements of FEL (free-electron laser) pulse power profiles. The use of machine learning to predict such profiles is an area of rapid development in the field. This work presents recent measurements and tests at the FLASH FEL at DESY of an image-based machine learning application developed to facilitate online FEL power profile reconstruction. The reconstruction has been performed using machine learning predictions of the longitudinal phase-space (LPS) of electron beams unaffected by the FEL process, originally measured using a transverse deflecting structure. The predictions were used in combination with longitudinal measurements of the LPS of the electron beam after lasing, which does not interfere with delivery to users, to reconstruct the FEL pulse. The results of the reconstruction process have been validated by comparison with a reference method which does not rely on machine learning.

INTRODUCTION

Free-electron lasers (FELs) provide ultrashort, high-brightness photon pulses that enable a wide range of scientific experiments. The temporal profile of these pulses, or the *FEL power profile*, is a key parameter for experiments using FEL light [1]. Direct measurements of single shot FEL power profiles remains a challenging task, often requiring invasive diagnostics and extensive use of dedicated machine time. Applications more suited to routine operations and online monitoring are in high demand [2].

When using the electron beam for FEL power profile measurements, one requires full longitudinal phase space (LPS) measurements, which is done at FLASH using a transverse deflecting structure (TDS) [3,4]. TDS measurements can be performed either on electron beams that generate FEL radiation (*lasing*) or those that do not (*non-lasing*). The FEL power profile can then be reconstructed from the differences between these two cases. Directly measuring FEL power profiles remains challenging since autocorrelation techniques, normally used for temporal characterization, lack sufficient nonlinear materials with high cross sections for XUV or X-ray photon energies. Methods that can deliver non-destructive, single-shot profiles, such as THz [5] or angular streaking [6], can be considered experiments themselves and often require extensive use of dedicated machine time.

There is a high demand for applications more suited to routine operations and online monitoring. Advancements in machine learning integration with electron diagnostics has opened up new possibilities for FEL power profile reconstruction. In particular, virtual diagnostics (VDs) focused on LPS predictions can be used in place of TDS measurements [7]. Such an approach can enable real-time estimation of FEL properties, and an application based on electron power profiles has been tested at FLASH, DESY [2].

In this work, also carried out at FLASH, we investigate a different approach. Rather than working only with power profile, we implement an image-based virtual diagnostic to predict the beam's full LPS distribution, before comparing with measurements during lasing for FEL power profile reconstruction. This is also compared directly with a non-machine learning reference method for reconstructing the power profiles.

EXPERIMENTAL SETUP

FLASH2 LPS Measurements

The FLASH FEL at DESY is driven by a superconducting linac with two stages of bunch compression, utilizing two stages of bunch compression in magnetic chicanes, resulting in kA-level peak currents. During the data acquisition, the electron beam was setup with a final energy of 920 MeV in the FLASH2 beamline and an RMS bunch length of approximately 180 fs. The linac was set up to produce a short bunch train of only two bunches in each shot, with a repetition rate of 10 Hz.

The FLASH2 TDS setup uses a X-band PolariX deflecting structure for beam streaking [8,9]. The 0.8 m PolariX structure is set up 2 m after the last FLASH2 undulator. After the RF streaking, the electron beam is diverted from the photon beam path by a 3.5°-bend magnet and during normal delivery, one bunch in the bunch train is deflected to a scintillating screen for imaging. For the experiments presented here, an on-axis screen was used, as a shortened bunch train was accelerated which would not damage the screen. The TDS setup was calibrated using scans of both the RF phase in the TDS and the current in the dipole deflecting onto the screen. For the data acquisition these procedures returned $0.89\,\frac{\text{fs}}{\text{px}}$ and 0.096 m for the shear parameter and dispersion on the screen respectively.

The data used in this study consisted of 5919 images collected without the beam lasing and 3146 images collected during lasing, all collected at a nominal setpoint for the FLASH accelerator. Lasing was controlled with a horizontal

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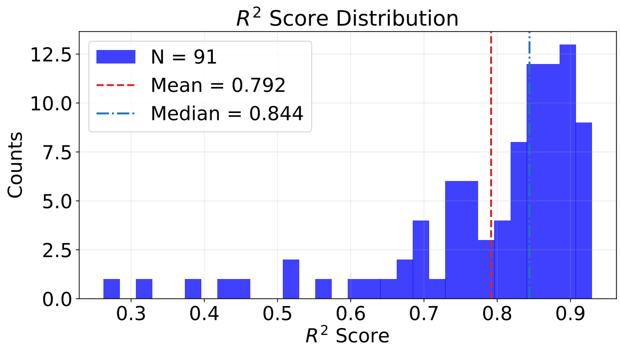

Figure 1: Coefficient of determination, R^2-score, of the VD predictions across the test dataset with 7 cases of $R^2 < 0$ removed.

kick to the beam trajectory, applied using steering magnets before the undulator section.

Virtual Diagnostic

The virtual diagnostic for this project consisted of an artificial neural network (ANN) set up to predict the full LPS of the beam, given a collection of 29 non-destructive inputs, including signals from 15 beam position monitors (BPMs), 9 bunch arrival monitors (BAMs), 4 bunch compression monitors (BCMs) and a charge transformer (CT). The final ANN consisted of two densely connected layers, followed by an up-sampling convolutional network, and had a total of 1.3 million trainable parameters. The ANN was trained using the ADAM optimizer and with mean absolute error (MAE) as the loss function. The trained VD achieved a final median coefficient of determination of 84.4±13.8% on a test dataset of 91 non-lasing images, randomly selected from the full non-lasing dataset. This smaller test dataset had 7 outliers of $R^2 < 0$ removed from the set. A histogram of the coefficient of determination, or R^2 across the test dataset can be seen in Fig. 1.

The goal was to leverage this VD to predict the non-lasing beam corresponding to a lasing TDS signal. This was done by training the VD using only non-lasing images, and then predicting new LPS distributions given the input signals for lasing beam configurations. As such, the final performance on this non-lasing dataset is only an indication of good performance in predicting non-lasing beams for lasing machine setups.

FEL Power Profile Reconstruction

The methodology for reconstructing FEL power profiles followed similar steps as outlined in [2]. The central energy was calculated for each slice along the longitudinal coordinate for the lasing and non-lasing LPS distributions. The lasing energy profile is then subtracted from the non-lasing one, thus providing a longitudinal distribution of the electron energy losses due to lasing. This energy loss profile is then multiplied with the bunch profile of the lasing bunch, thus providing the final power profile of the FEL radiation [10].

In order to validate the virtual diagnostic approach, the results are compared with an established non-ML technique to compare lasing on and lasing off data. For this approach, the bunch profiles of all lasing and non-lasing LPS distributions were collected, clustered into groups, and the average properties of these non-lasing data are compared to those lasing. The group with the highest similarity for each lasing profile was chosen for the FEL power profile reconstruction.

In order to demonstrate the accuracy of the predicted profiles, we compare these *VD-based* and *correlation-based* FEL power profile reconstructions. In order to have a consistent and physically motivated scale to these power profiles, their total integral was normalized to the recorded signal from a gas-monitor detector (GMD) present in the FLASH2 beamline. The GMD provides a pulse-resolved, absolute measurement of the total FEL pulse energy via photoionization of a gas [11].

RESULTS

An example of the final prediction of a non-lasing bunch with its corresponding lasing bunch and FEL power profile reconstruction can be seen in Fig. 2. In the last plot, the two FEL power profile reconstructions are shown, using either the VD- or correlation-based non-lasing LPS for the comparative reconstruction. The specific case shown in this figure represents the median case in terms of correlation between the two reconstructed FEL power profiles across the dataset. We can see that the final FEL profiles are quite similar, with some differences in the very head and tail of the beam, where the VD-case predicts some increases in FEL power which do not appear in the correlation-based case. This appears to be an artifact arising from a failure of the VD to predict the fine structure in the very head and tail of the beam, and the network's performance in these low-intensity areas will be highly dependent on the image pre-processing.

Figure 2 shows only a single case of the different reconstructions, and for a clearer overview of all the FEL profiles, one can look at the mean profiles, calculated based on each of the FEL profiles reconstructed using both techniques. This is shown in Fig. 3, along with shaded regions for one standard deviation of the distribution of power along the profile. Here we can see that the smaller issues present in the VD technique reemerges across the full dataset, i.e., we can see an increased uncertainty in the head of the beam, although we see here that this is present in profiles reconstructed with both techniques. Here we can also more clearly see a second artifact at the tail of the bunch, where some lasing appears when using the VD reconstruction. This is an artifact and could likely be filtered out.

CONCLUSION AND OUTLOOK

The final results of this project demonstrate the feasibility of leveraging ML-based virtual diagnostics trained on non-destructive beam data for FEL power profile reconstruction. While such approaches have been tested in the past, here we show the use of full non-lasing LPS predictions to enable non-invasive FEL profile reconstruction. In comparison

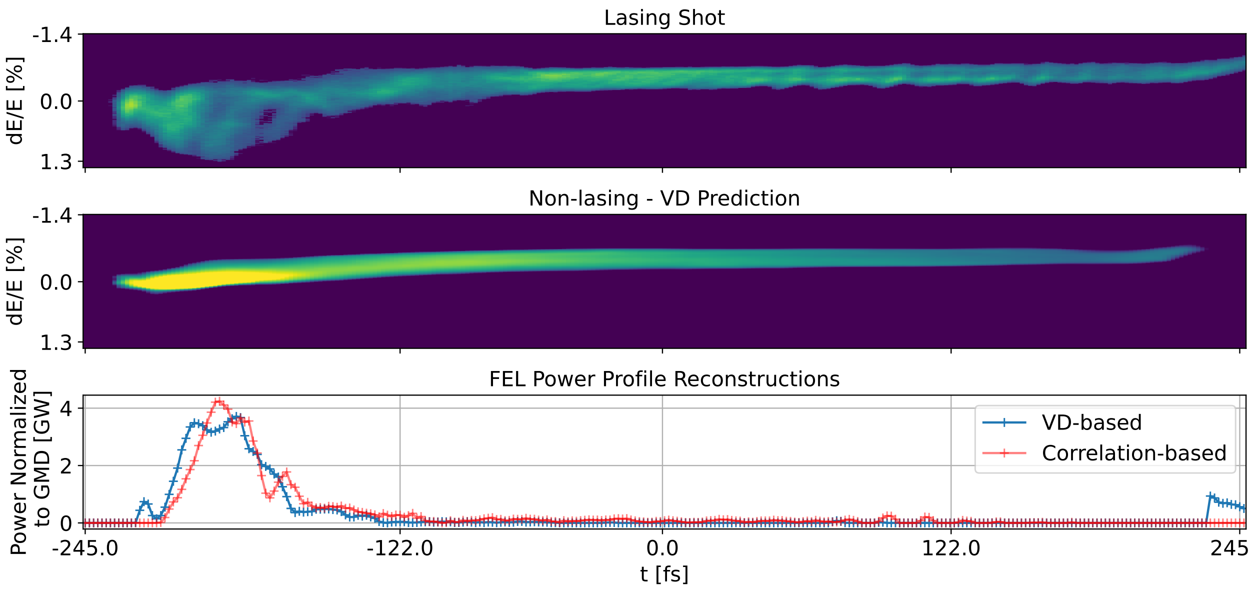

Figure 2: The LPS distribution of a lasing shot and its corresponding non-lasing shot based on a VD prediction. Also plotted at the bottom is the reconstructed FEL power profiles, using comparisons between lasing and either the non-lasing shot from VD prediction or from cross-correlation selection. The specific case was selected at the median correlation between the two FEL power profile reconstructions.

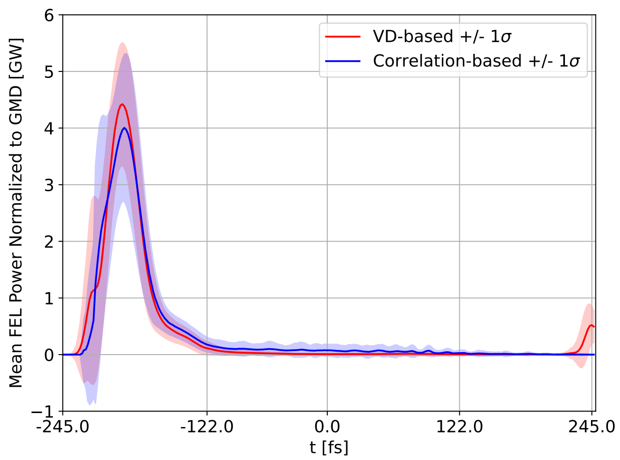

Figure 3: Mean of the FEL power profile reconstructions based on both virtual diagnostic predictions and correlation selection of non-lasing shots. Plotted with shaded regions representing $\pm 1\sigma$.

with a correlation-based reference method the VD-based approach shows a good overall agreement, suggesting that the VD is capable of capturing the key features relevant to FEL power.

There are some drawbacks to the VD-based techniques, as artifacts did appear in the final FEL power profiles, mainly in the head and tail of the bunch where the virtual diagnostic struggles to reproduce the fine structures of the phase space distribution. In contrast, the correlation-based method provided more stable behavior, although this method had drawbacks, mainly in the reliance on a very large non-lasing dataset.

The presented VD approach is only an initial test case with a limited dataset, but already offers a fast and scalable alternative to traditional methods which could be modified and improved for online monitoring of the FEL power profile. The few discrepancies present in the results could likely be alleviated with fine tuning of the models.

Future work could focus on improved robustness of the VD model, for example with improved network architecture or training procedures. Naturally, more expansive and detailed datasets are always an improvement for ML-based applications. If extensive enough data was made available on a variety of FEL setups, then a general network for predicting non-lasing beams could be fine-tuned for specific beamtimes and accelerator conditions. For a future reliable, real-time FEL power profile diagnostic, work is required in validating the VD at different settings and during drifts in the machine working point, as well as developing a final implementation in control rooms.

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