ANOMALY DETECTION AND DENOISING OF NON-GAUSSIAN BEAMS USING 2D IMAGE RECONSTRUCTION TECHNIQUES BASED ON DEEP LEARNING

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Abstract

Automatic image reconstruction tools are essential in fields such as physics, astronomy, and biology. In particle accelerators like CERN's LHC, they are particularly important for evaluating beam quality through beam position, profile, and emittance measurement. Traditional analysis tools no longer meet the accuracy and efficiency demands of future facilities. A new AI-based digital tool is used for 2D transverse phase-space distributions denoising improving the accuracy of RMS emittance measurements. Our focus was to enhance beam halo characterization, ultimately contributing to reduce transport losses, and enabling more sustainable accelerator operations. Challenges are related to noisy experimental data, lack of ground-truth reference images, noise model, and limited training datasets. Our unsupervised deep convolutional neural network (DCNN) can denoise a single image using only itself as input thus greatly improving the accuracy of emittance measurement.

INTRODUCTION

Accelerator facilities increasingly depends on advanced beam-diagnostics capable of supporting stringent performance, and reliability requirements. As beam intensities and stored energies rise, precise control of beam losses becomes essential for machine protection, operational efficiency, activation reduction, and long-term environmental sustainability. These goals require high-accuracy, high-dynamic-range measurements of beam position, profiles, and phase-space distributions. In particular, resolving low-intensity beam halos often five orders of magnitude below the core remains a major challenge due to sensitivity limits, and background suppression. Similar to trends in medical imaging, or Earth-observation systems, accelerator diagnostics demand sophisticated data-processing methods. Traditional analysis techniques appear insufficient for the needs of modern machines [1-2]. AI-based approaches offer promising capabilities for denoising, feature extraction, and multidimensional parameter inference. This paper reviews the state of the art in image-based beam-diagnostic analysis and presents a new method using convolutional filters and NN architectures to enhance measurement fidelity and robustness for future accelerator operation.

BEAM DISTRIBUTIONS

Among the usual beam quality diagnostics, the transverse profile, position, and emittance play a key role in the control of the accelerators and the definition of their luminosity and brightness [3-9]. Beam halo depends on the tails in transverse distribution produced by optics mismatch, field and beam dynamics nonlinearities. The halo is characterized by a variable particle density, which follows a distribution often likened to a Gaussian, which extends well beyond the core of the beam [10-13], but due to the number and complexity of interactions between it and its environment, can take on very different appearances. Emittance growth due to tail increase feeds beam losses and requires six-dimensional beam matching between the different sections of the accelerating structure. This optimization process allows a smaller volume in the 6D phase space, thus increasing beam brightness and reduction of losses [14-15]. These malfunctions induce cascading effects such as quench of SRF cavities, overheating of beam transport equipment, melting, sputtering, activation, etc. The measurement of the halo distribution requires the detection of electric charges over a wide dynamic range up to six orders of magnitude. One of the fundamental challenges lies in distinguishing noise from the true signal in the absence of prior knowledge of the noise distribution. This difficulty is exacerbated by variable experimental conditions and fluctuating background noise, which hinder the development of universally applicable denoising strategies. Classical statistical methods are still widely employed across operational particle accelerator facilities to extract information from beam diagnostics data. However, these approaches encounter significant limitations when confronted with noisy signals, irregularly shaped beam cross-sections, non-elliptical or non-Gaussian phase-space distributions, non-uniform densities, or parasitic contaminating beams [16-18]. The most common approach for RMS emittance determination relies on applying an arbitrary threshold to separate useful signal from background noise. However, even modest noise levels or the absence of minimal halo signals below 10^{-4} of the total beam intensity can introduce substantial bias, with RMS errors exceeding 100% in extreme cases [19-21].

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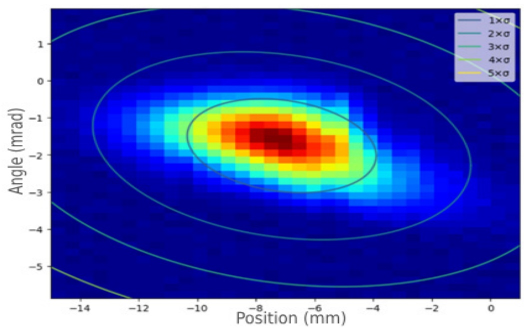

Figure 1: Two-dimensional trace-space representation of transverse emittance obtained with IPHC's scanner.

DATA ANALYSIS AND IMAGE PROCESSING

A comprehensive analysis of two-dimensional phase-space distributions was performed on a large corpus of emittance images to ensure that the denoising tool is trained on representative, diverse, and high-quality inputs, see Fig. 1 [22]. Due to the substantial variability in image properties including size, beam shape, noise distribution, spatial scale, resolution, and region-of-interest centring, global normalization across the entire dataset proved infeasible. This heterogeneity reinforced the choice of an unsupervised learning strategy, in which denoising is performed on a per-image basis without relying on a universal normalization scheme [23-28]. Such an approach is particularly well suited to accelerator diagnostics, where measurement conditions can vary widely and unpredictably across facilities and operational regimes. All the data are displayed in grey scale, stored and analysed at pixel level with third rank tensors in order to perform inverse problem-solving type treatments (classification, clustering, segmentation, pattern recognition, denoising, etc.). Colours are only used to improve contrast and readability of the images. The model developed to denoise and reconstruct the images is a deep convolutional neural network (DCNN) with a UNET encoder–decoder structure and skip connections [29], see Fig. 2, complemented with new early stopping strategies (ES), and inspired by the Deep Image Prior (DIP) framework [30-33]. In these architectures, each convolutional layer comprises a set of learnable filters, where each filter generates a feature map whose individual pixels function as neurons sharing identical parameters through weight sharing. This design preserves spatial locality and enables efficient representation learning across the image domain.

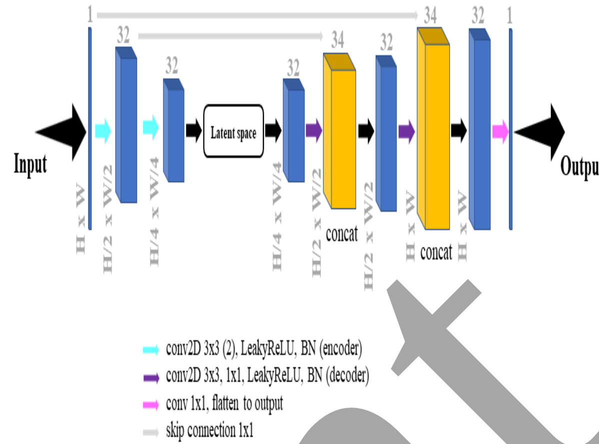

Figure 2: Architecture of the DCNN model (UNET structure) with two convolution blocks for down sampling and two for up sampling, two layers of 32 filters each, and 2 skip connections.

RESULTS

In order to ensure that model behave in accordance with our goals, a few evaluation metrics with physical meaning were used to align the results with physics. They are based on the beam intensity transverse profile and on the RMS-emittance. After image reconstruction, the effective resolution is substantially enhanced, with detectable transverse amplitudes extending beyond seven standard deviations from the beam core in the best case, see Fig. 3. At this level of sensitivity, the system is capable of resolving particle populations whose local densities fall below 10−4 of the total beam intensity, thereby capturing the outermost regions of the halo.

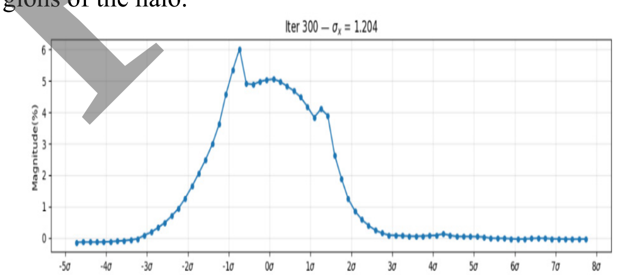

Figure 3: Beam profile reconstruction obtained with DCNN model and showing extended radial resolution.

DISCUSSION

Our DCNN framework is combined with a loss function integrating quantitative physics and qualitative human perception resulting from a thorough heuristic approach. During training, the network adjusts its weights to restore a noisy image by first capturing the underlying structure before adapting to the noise. This property enables effective denoising of the emittance figures produced with a large variety of beams and facilities without reliance on external datasets. The approach preserves fine details and local textures with high fidelity, even in the absence of ground truth/noisy pairs or external supervision, see Fig. 4. Initial results showed that standard quantitative metrics were insufficient for evaluating perceived image quality in the absence of ground truth. Furthermore, early denoising attempts failed to significantly improve RMS emittance calculation. To address this, regularization strategies are incorporated as ES mechanisms to prevent overfitting and optimize the denoising process. By integrating these into the training loop, we aimed to identify the optimal stopping point for denoising each image. The number of iterations at which ES occurs shows a strong correlation with the evolution of RMS emittance. This suggests a clear relationship between the ES iteration count and emittance behaviour, indicating that the combination of DCNN and ES is a promising approach for improving the accuracy. The proposed approach is intentionally model-agnostic, enabling its application across a broad range of image-processing-based diagnostics and facilitating adaptation to heterogeneous data sources. While regression architectures are naturally suited for data-generation tasks and classification networks can support denoising, our context requires a more granular strategy focused on pixel and feature-level detection to reliably identify spatial structures. The choice of convolution-kernel size plays a central role, as it must balance the recovery of fine details with the ability to capture larger-scale relationships between regions, an aspect reminiscent of Gestalt principles in visual perception. A further challenge arises from the presence of outliers that may share similar amplitudes or morphological features with the true signal, complicating the consistency of the effective SNR and demanding robust filtering strategies.

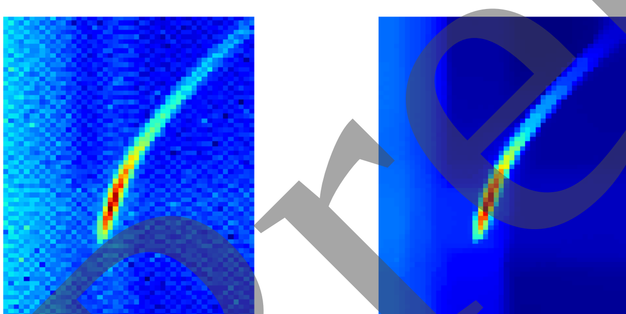

Figure 4: Emittance figure restoration (image-based agnostic processing): degraded scan (left), cleaned version represented (right).

CONCLUSION

The reconstruction of beam emittance images using a DCNN framework from computer vision, combined loss function, and metrics with physical meaning, has led to a substantial improvement in halo resolution through effective noise suppression and signal capture from the background. These results were obtained under highly unfavourable conditions, including very low SNR, targets with heterogeneous and irregular shapes, non-Gaussian transverse distributions, and small, non-annotated datasets. The proposed solution is also characterized by its frugality: it requires minimal computational resources, and does not rely on cloud computing or datacenter, making it a promising tool for beam diagnostics and other applications where ground-truth data and large training sets are unavailable. The encouraging results obtained here motivate more systematic investigations and the establishment of a comprehensive benchmarking framework. A particularly relevant direction for future work is a controlled variational study in which beam parameters specifically diameter, intensity, and resolution are incrementally modified. Such perturbations would generate large sets of images spanning multiple configurations. Although inherently time-consuming, this procedure would produce paired datasets designed to challenge the model with diverse representational conditions. These datasets could then serve as a foundation for training supervised models, enabling rigorous comparative evaluations and further improving the robustness of AI-based beam-diagnostic tools. Together, these considerations highlight the need for flexible, interpretable, and noise-resilient image-analysis pipelines capable of supporting next-generation beam-diagnostic systems.

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