Innovations for a Sustainable Tomorrow

LIV.INNO

Machine Learning for Beam Profile Reconstruction

Q. Xu[1,2,3], A. Hill[1,2], H. Zhang[1,2], G. Trad[3], S. Burger[3], M. Bergamaschi[3], A. Gilardi[3], F. Roncarolo[3] and C. P. Welsch[1,2]
[1]University of Liverpool, UK , [2]Cockcroft Institute, UK, [3]CERN, Switzerland

Transverse beam profile monitoring is essential for **safe** and **efficient** accelerator operation. In high-radiation environments such as beam dumps, cameras **degrade rapidly**. To address this, a single multimode fiber (MMF) transmission system was proposed to transport scintillation light from a screen to a remote camera. Because multiple guided modes are excited and coupled during propagation, the fiber output does not preserve the image and requires reconstruction. This contribution evaluates reconstruction models for recovering the original transverse beam distribution from MMF output. Using data from the MMF-relayed Chromox screen campaign at CERN's CLEAR facility [1], the study compares models in terms of reconstruction error, convergence speed, and run-to-run stability. The results indicate robust options for radiation-tolerant, MMF-based transverse diagnostics.

Experiment and dataset

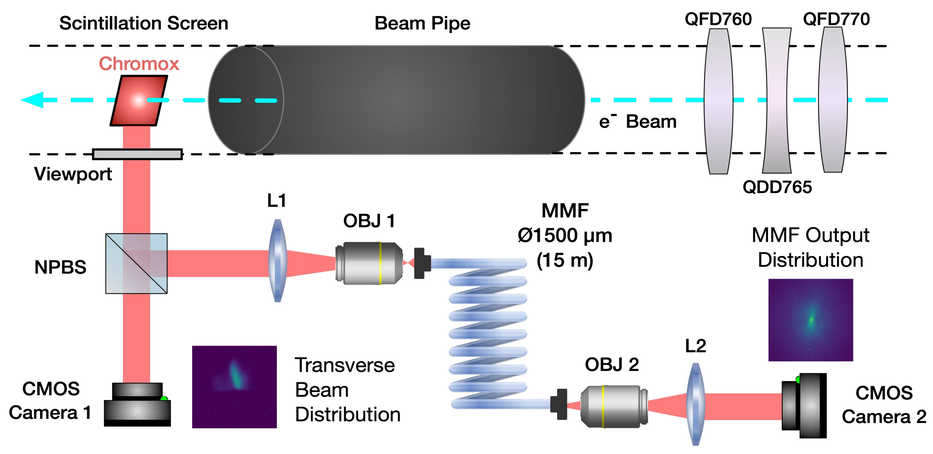

Fig. 1 Schematic of dataset collection at CERN CLEAR. An electron beam is adjusted by varying the strengths of quadrupole and correctors to generate diverse transverse profiles on a Chromox scintillating screen. A reference CMOS camera (CMOS1) records the direct beam image through a viewport. In parallel, a beam splitter directs part of the scintillation light into a multimode fiber via coupling optics, and a second camera (CMOS2) captures the scrambled fiber output. In total 6,257 sample pairs were collected.

ML models and training

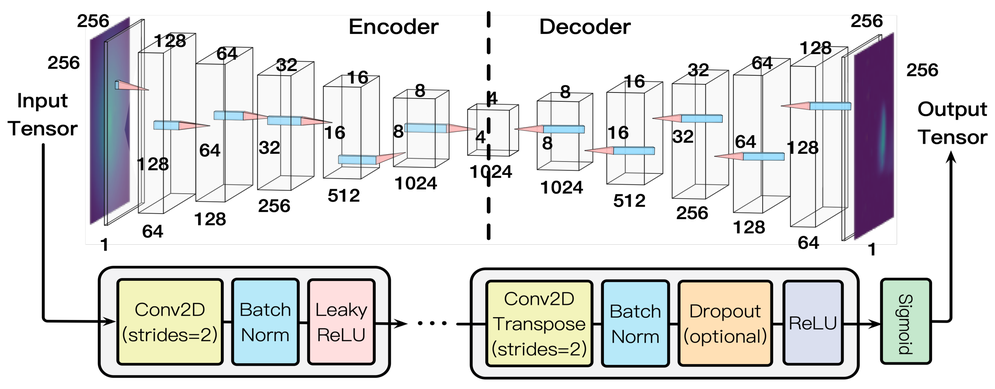

Fig. 2 Architecture of the 2D convolutional autoencoder for MMF image reconstruction. Stride-2 convolutions compress spatial dimensions to 4×4 bottleneck feature maps, replacing pooling layers. Skip connections are removed for better generalization.

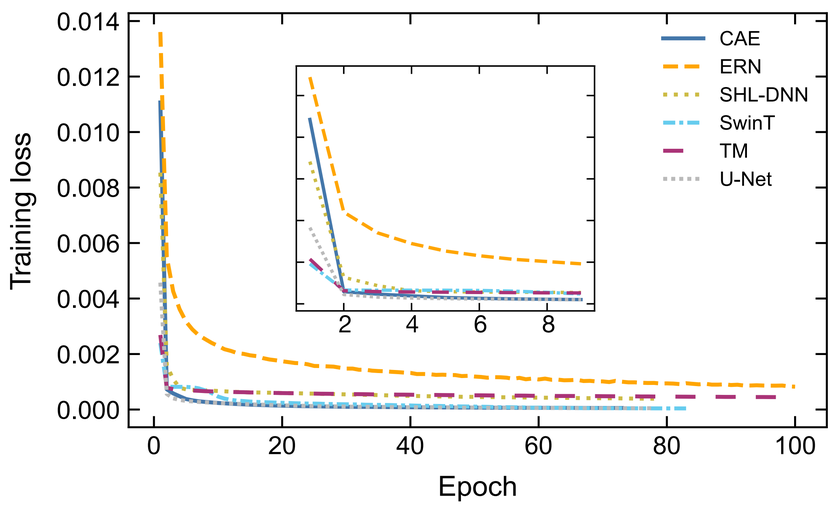

Fig. 3 Training loss over 100 epochs with early stopping. Loss is pixel-wise MSE for image-based models and transverse beam parameter-wise MSE for ERN. The inset shows a zoom of the initial epochs from 1 to 10.

Signal reconstruction result

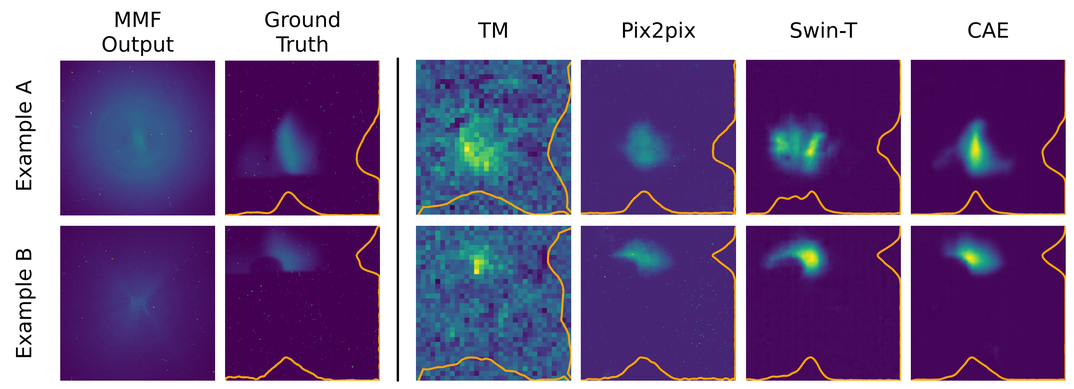

Fig. 4 Representative reconstructions of two non-Gaussian test samples. Each row from left to right: fiber output image (model input), ground-truth transverse distribution, and reconstructions from four selected models. Orange lines indicate horizontal and vertical beam profiles.

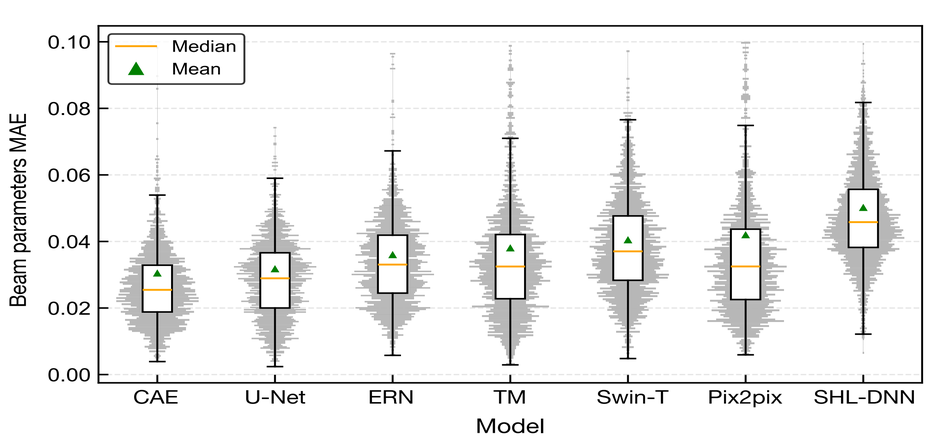

Fig. 5 Box plots of reconstruction MAE distributions across models on the test set. Each box shows the error spread with mean (green triangle) and median (orange line), illustrating relative reconstruction performance.

Model	MAE	Size [MB]	Training Time [min]
CAE	0.030 ± 0.033	71	59 ± 18
U -Net	0.032 ± 0.031	83	311 ± 13
ERN	0.036 ± 0.024	46	54 ± 25
TM	0.038 ± 0.033	256	61 ± 6
Swin-T	0.040 ± 0.024	150	153 ± 31
Pix2pix	0.042 ± 0.046	104	155 ± 89
SHL-DNN	0.050 ± 0.030	80	17 ± 1

Table. 1 Final average MAE on the test set (mean ± std over three runs with different seeds affecting model weights initialization and dataset partition), along with model size and total training time (mean ± std over runs) on the HPC.

Conclusion and future work

The customized convolutional autoencoder achieved consistent reconstruction of transverse beam profiles from MMF-scrambled images, supporting further development of remote beam diagnostics.

- Future work will include systematically examine temperature and geometric variations effects to the fiber.
- Radiation degradation: Investigate degradation effects on the MMF.

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