Development of a multimode fiber system for remote transverse beam imaging at CLEAR

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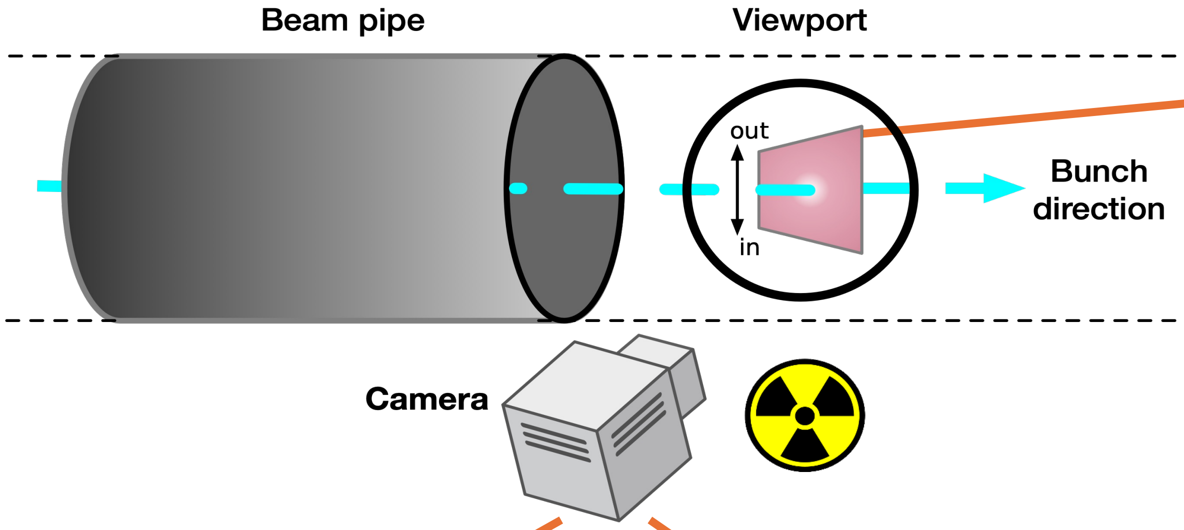
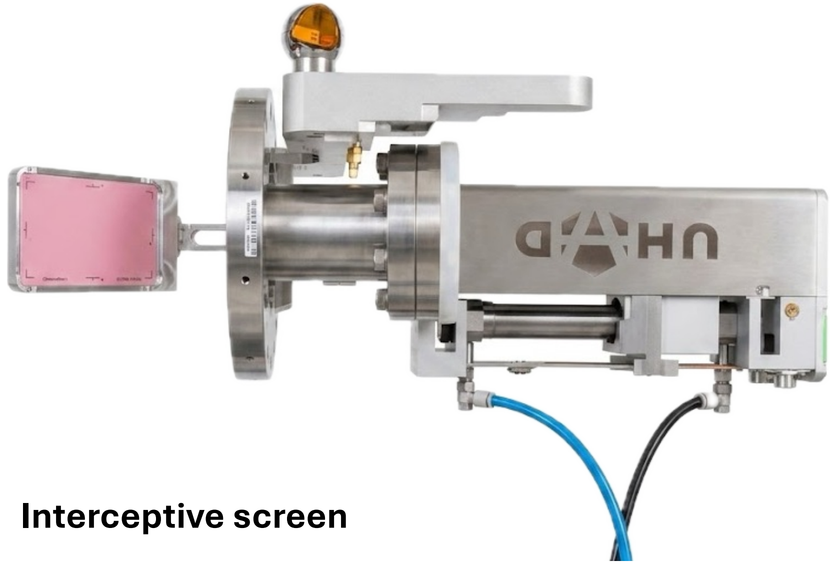
Outline

1. Background
2. Limitations of beam data
3. Lab proof of concept with synthetic data
4. Model evaluation
5. Cross-domain training: preliminary results

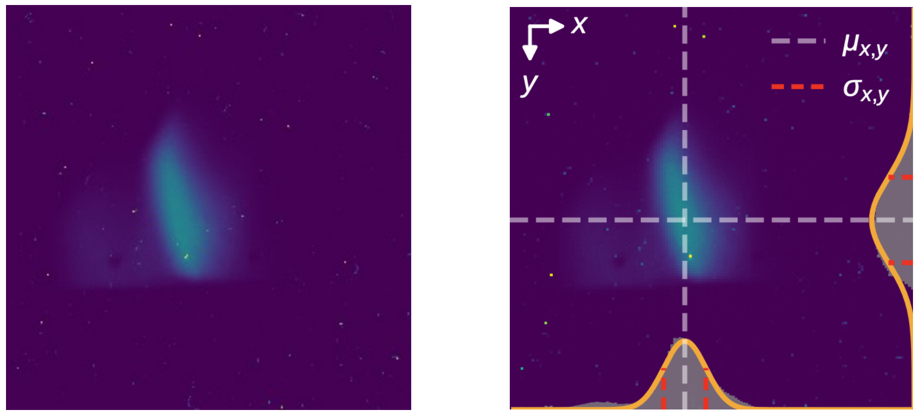
Transverse beam imaging in radiation environments





Interceptive screen

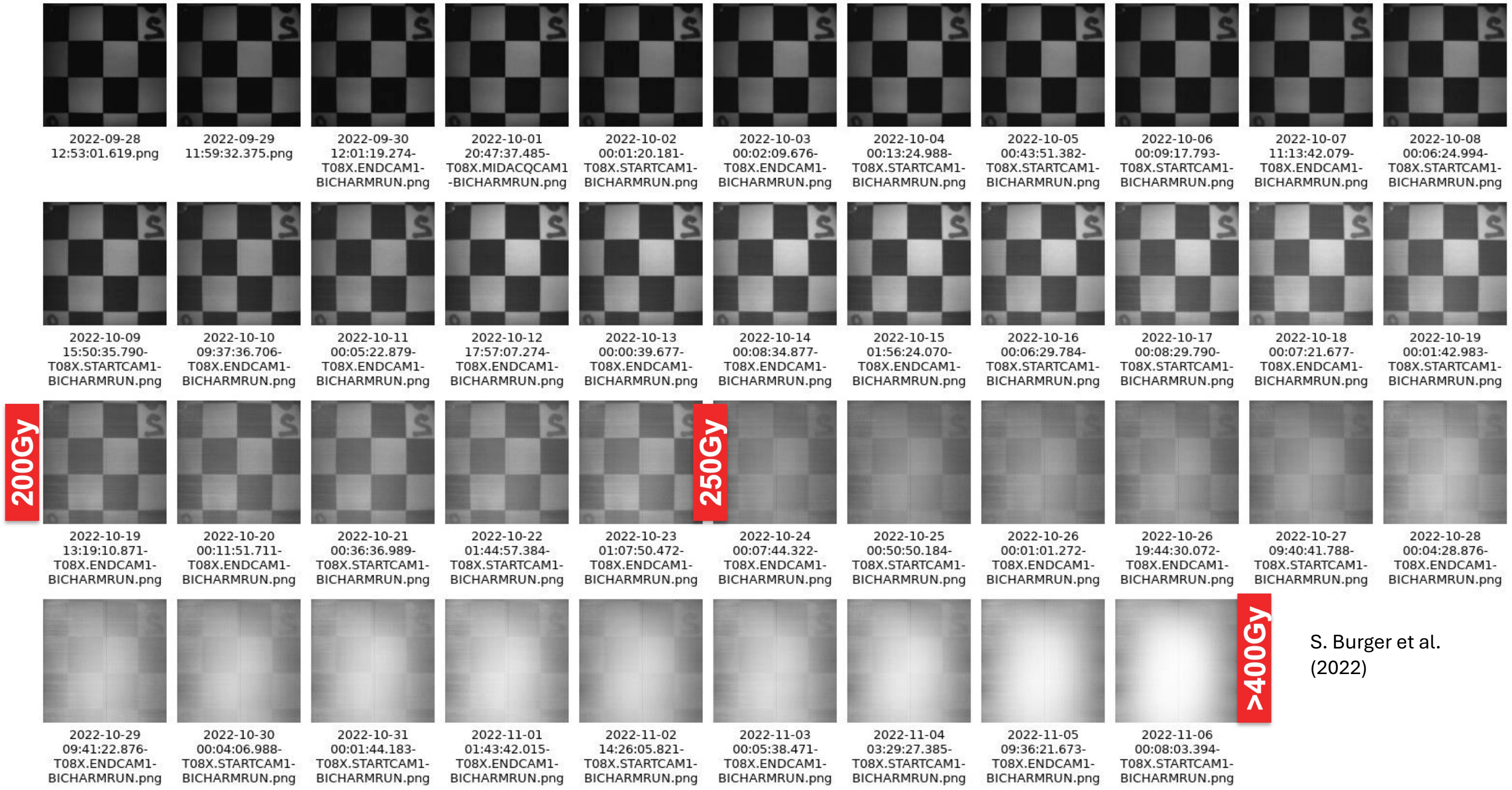
Radiation-hard tube-based camera



Transverse beam distribution

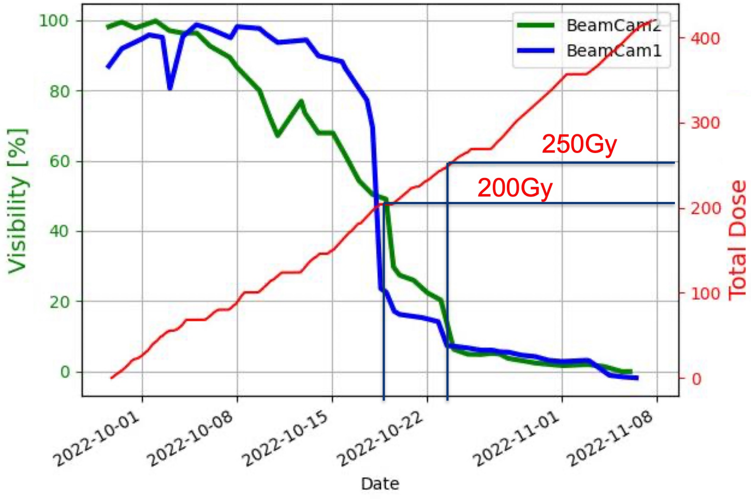
Beam parameters

What happens to a camera under radiation?



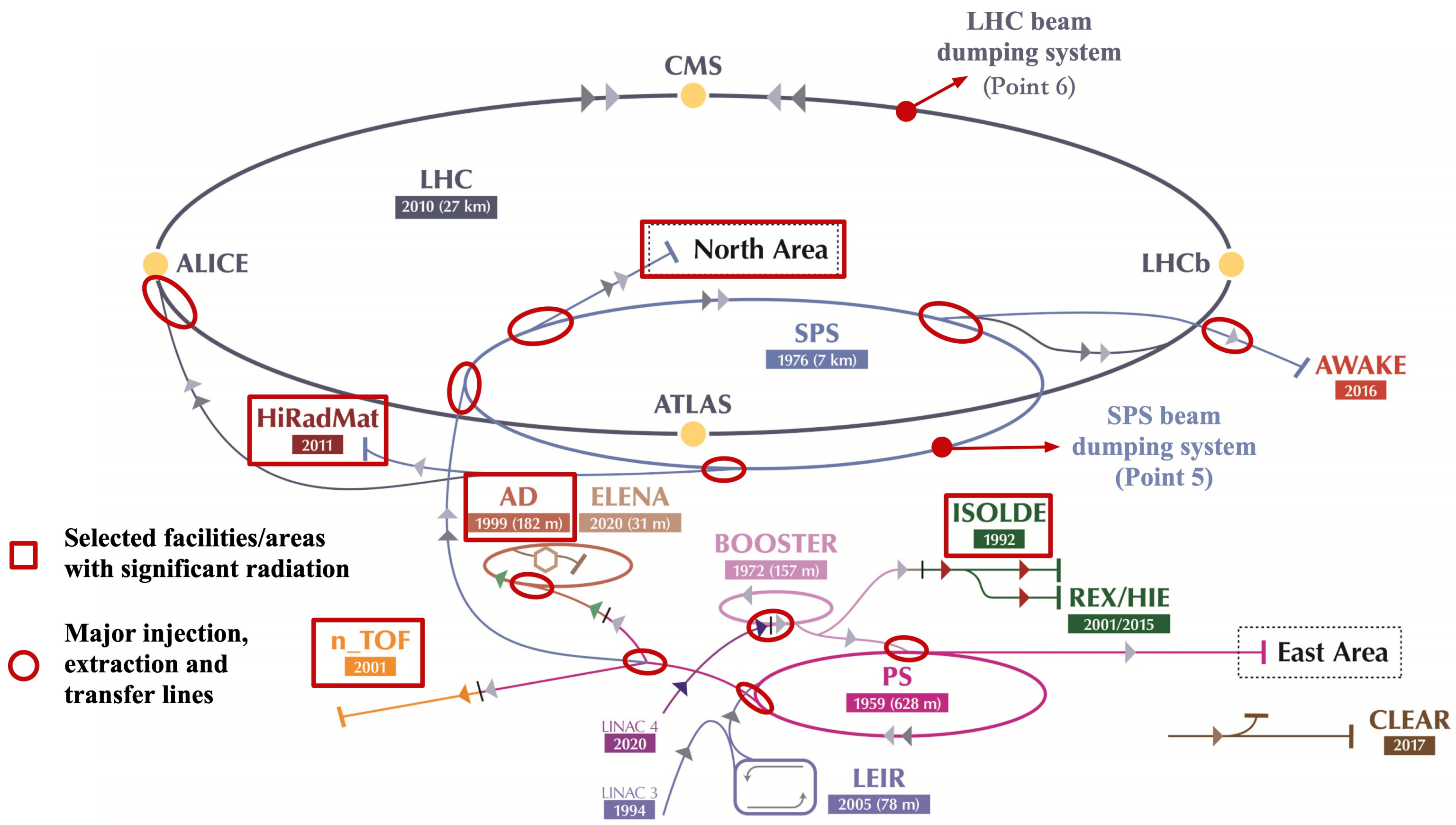
S. Burger et al. (2022)

$$\text{Visibility} = \frac{I_{\max} - I_{\min}}{I_{\max} + I_{\min}}$$



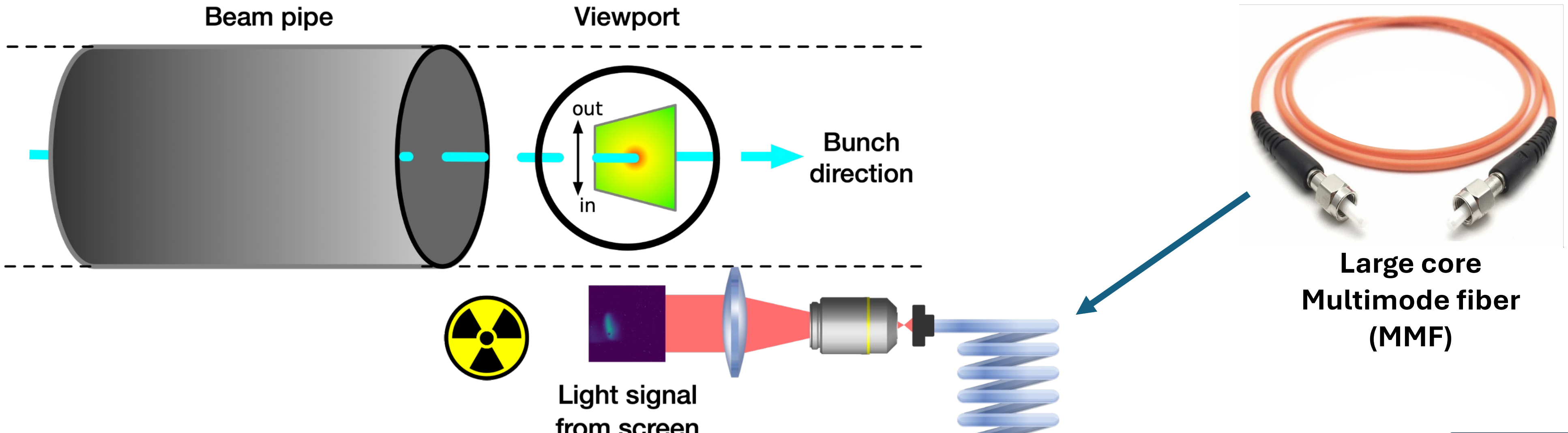
- CERN-MCSE BeamCam prototypes (radiation-tolerant) tested at CERN CHARM (R&D); image visibility versus Total Ionizing Dose (TID).
- Commercial cameras: **~100 Gy**; BeamCam imaging: **~250 Gy,** while some BTV locations can reach **kGy scale** TID.

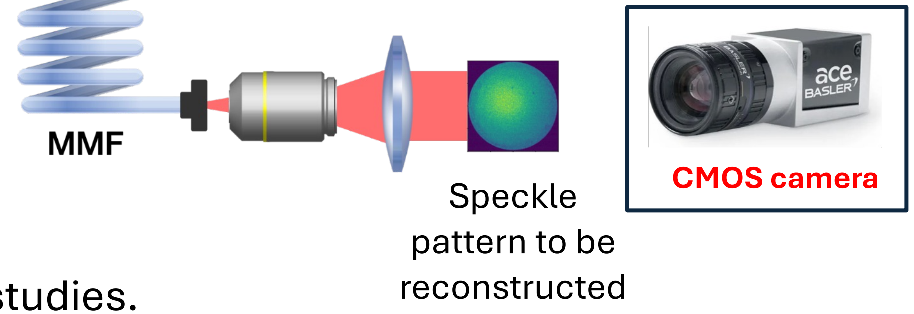
Radiation limits imaging in many accelerator areas



- **Impact** : ~ **200** beam imaging systems across CERN; ~ **2/3** potentially radiation affected.
- **Examples**: beam dump and fixed target areas are exposed to very high radiation levels.
- **Challenge**: Radiation hard vidicon tubes are **no longer produced worldwide**.

Remote beam imaging with a single multimode fiber

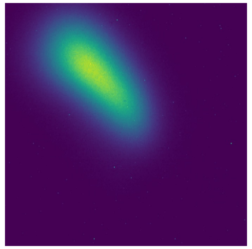


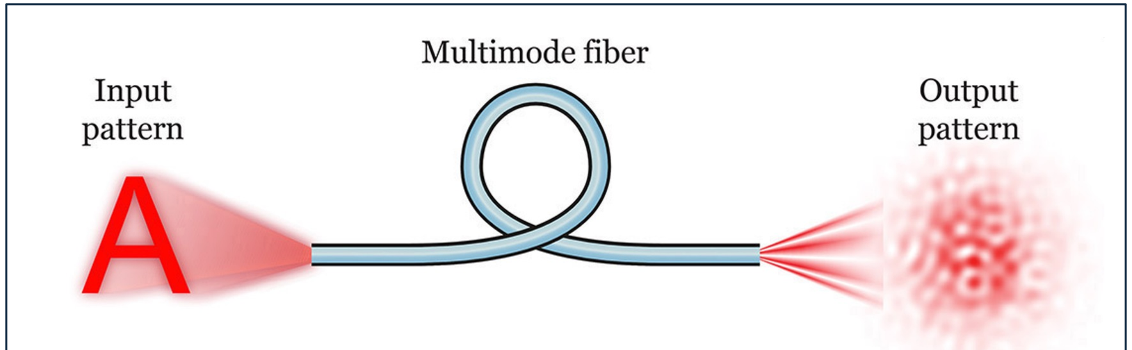


Why multimode fiber?

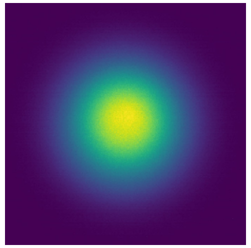
- Efficient waveguide over tens of meters.
- **Simple, modular**, and **easy to install or replace.**
- Many guided modes can carry rich **spatial information**.
- Radiation response documented in previous irradiation studies.

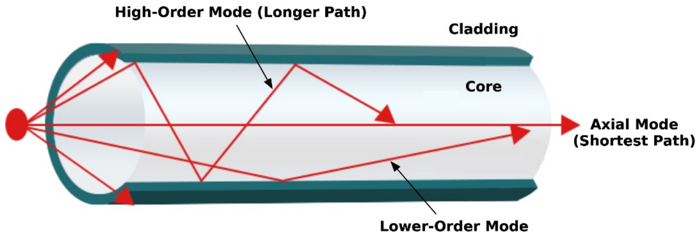
Multimode fiber propagation scrambles the input image



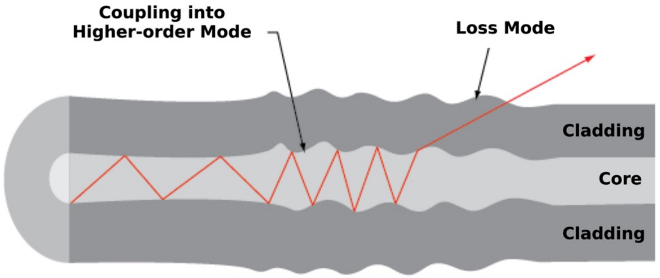


(Psaltis and Moser, 2016)

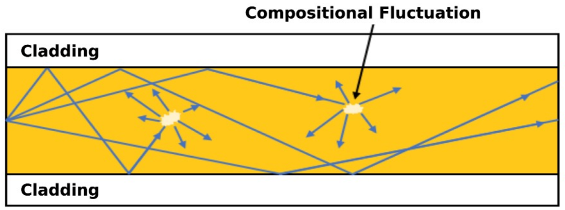




Modal dispersion



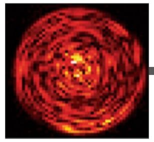
Mode coupling



Scattering

A brief history of multimode fiber image reconstruction

- Selected milestones, timeline not to scale



Phase Conjugation

1967

Wavefront Shaping

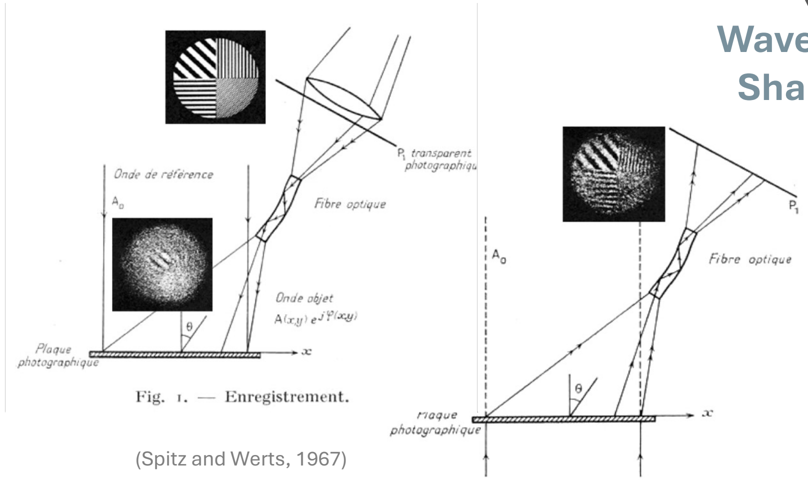


Fig. 1. — Enregistrement.

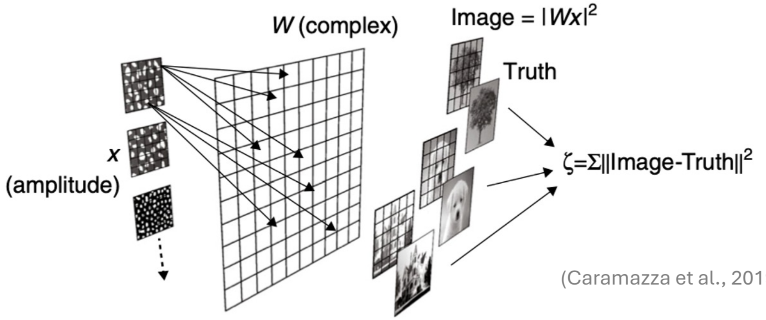
(Spitz and Werts, 1967)

Fig. 2. — Restitution.

Computational Reconstruction

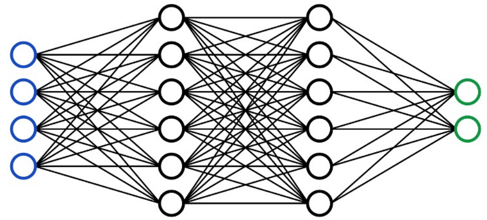
Transmission Matrix

2010

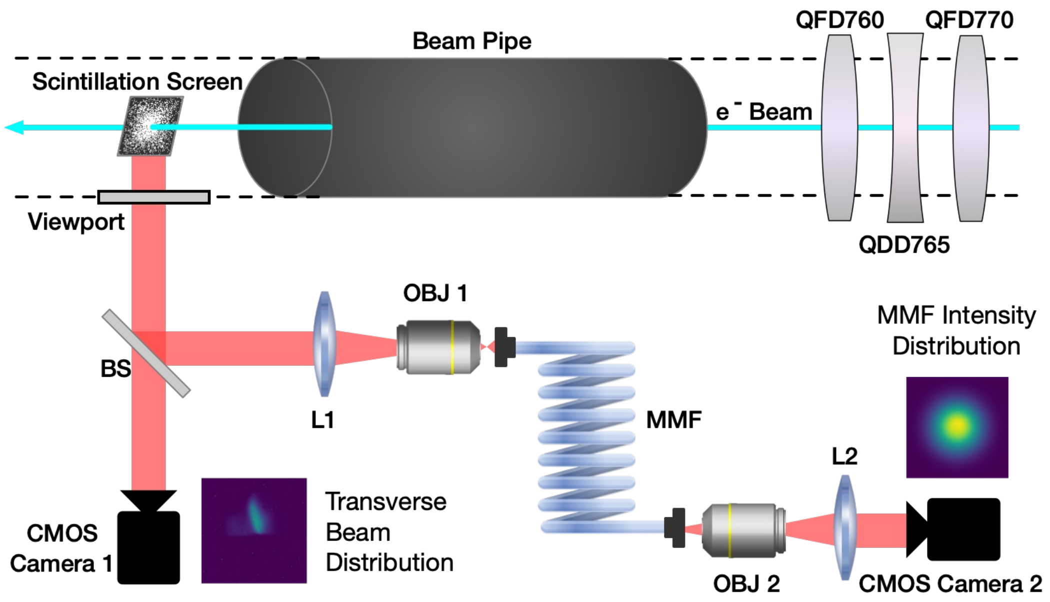


(Caramazza et al., 2019)

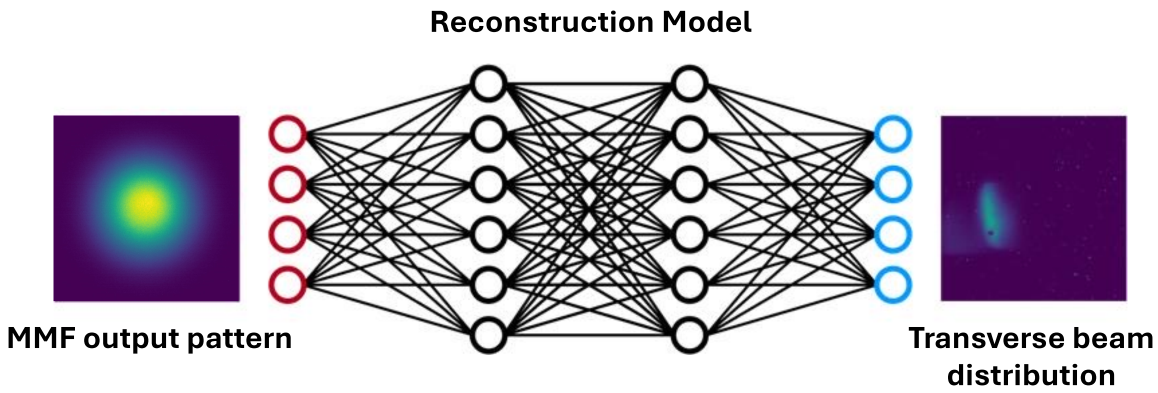
Machine Learning



Learning directly from beam data?

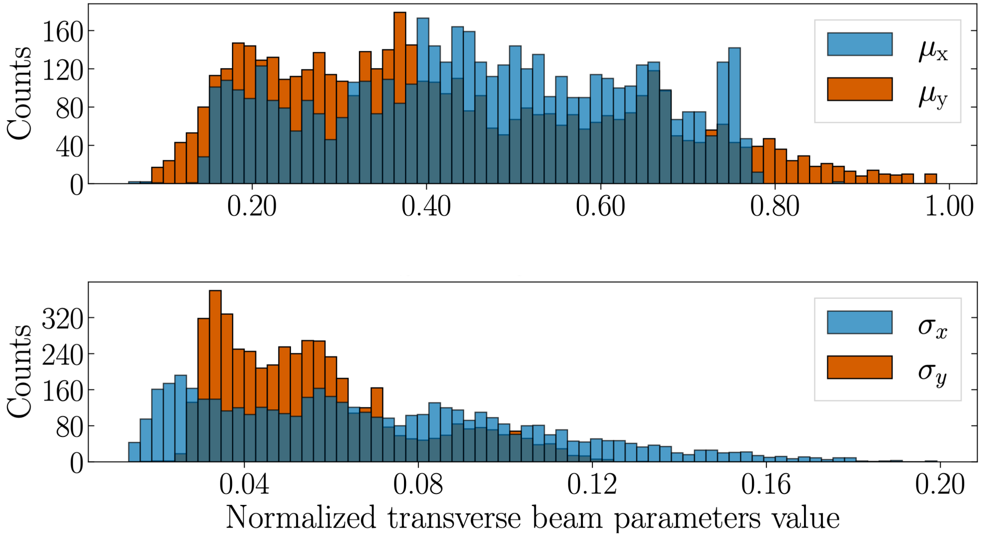


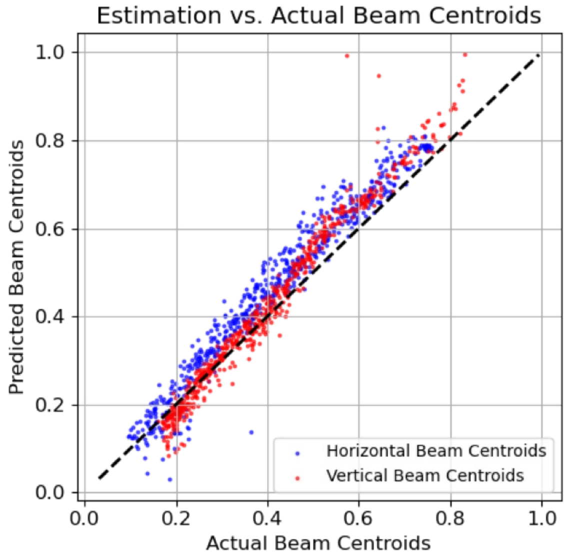
Collect paired beam and fiber output images for training and evaluation

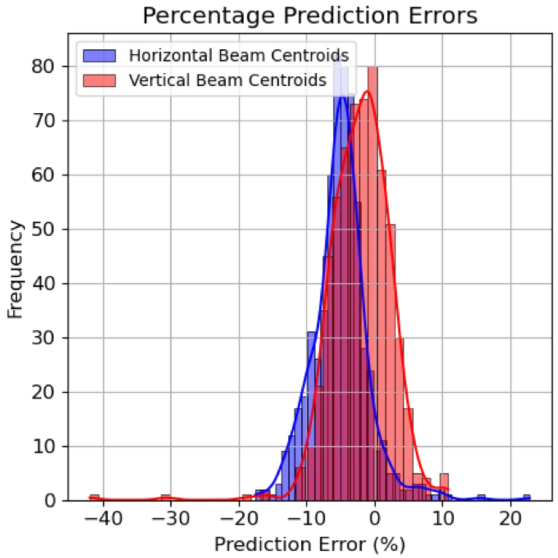


Reconstruct the beam image from the fiber output with a neural network

Training data is the key bottleneck

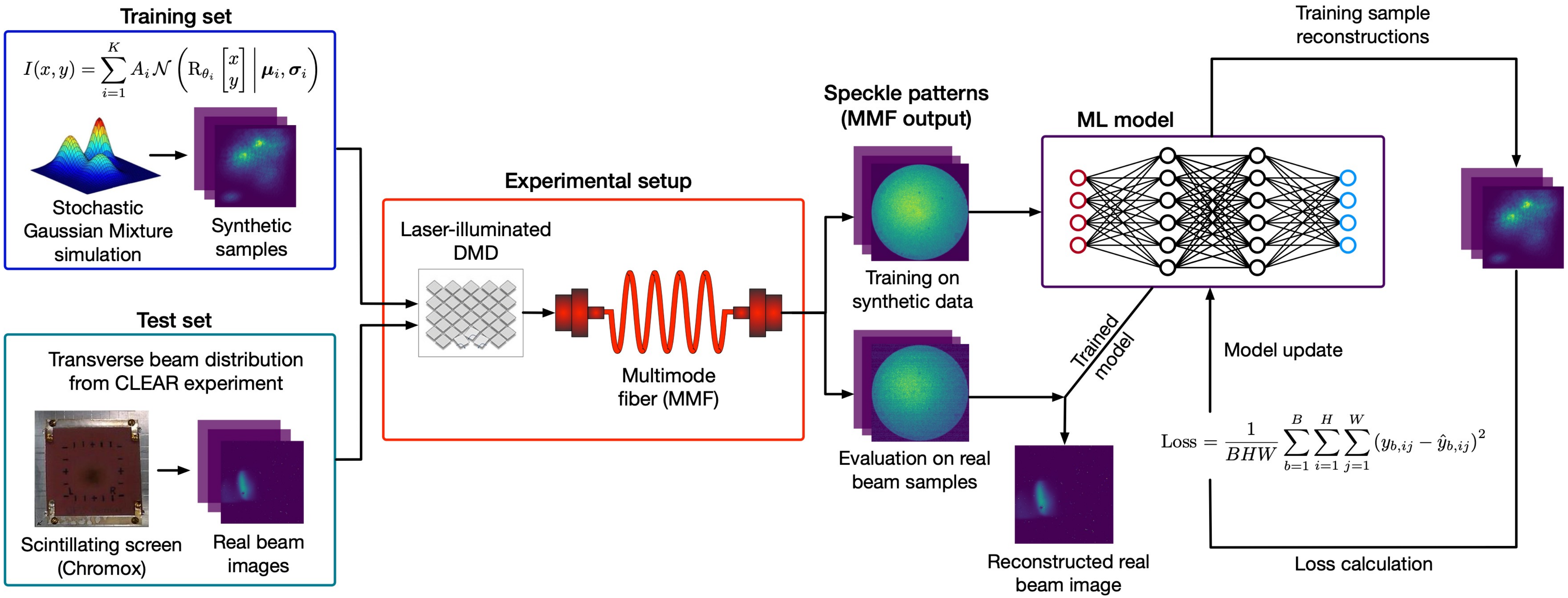






- **Limited and biased data**: restricted beam time and uneven coverage of beam conditions.
- **Radiation exposure**: collecting more beam data increases exposure of the reference camera.
- **Poor parameter coverage**: sparse or imbalanced data can reduce generalization and introduce prediction bias.

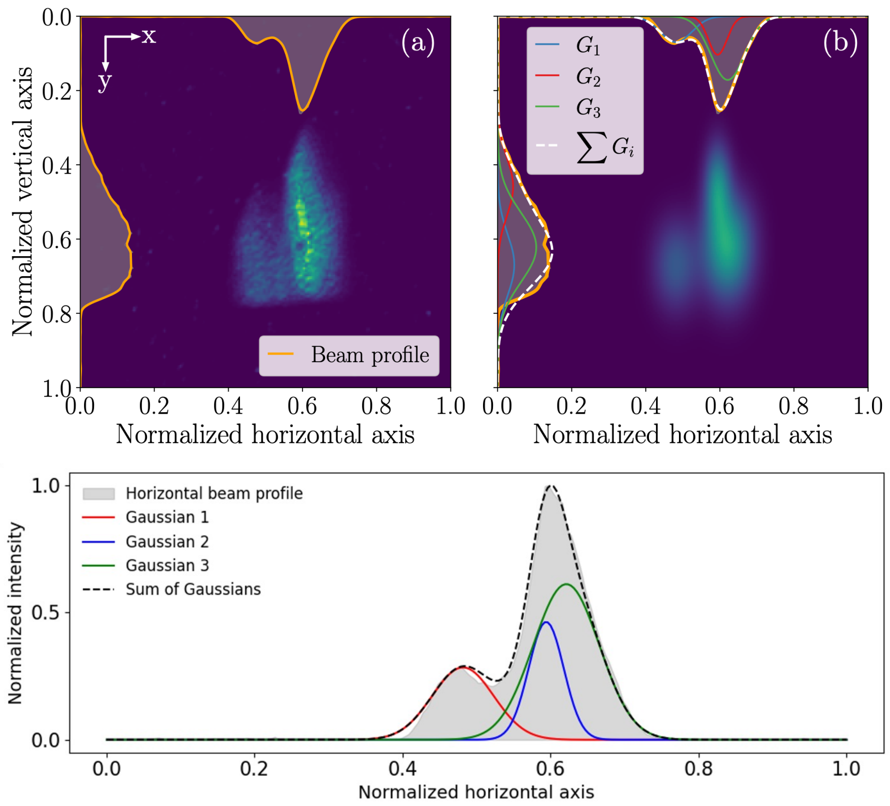
Synthetic data expand the training space



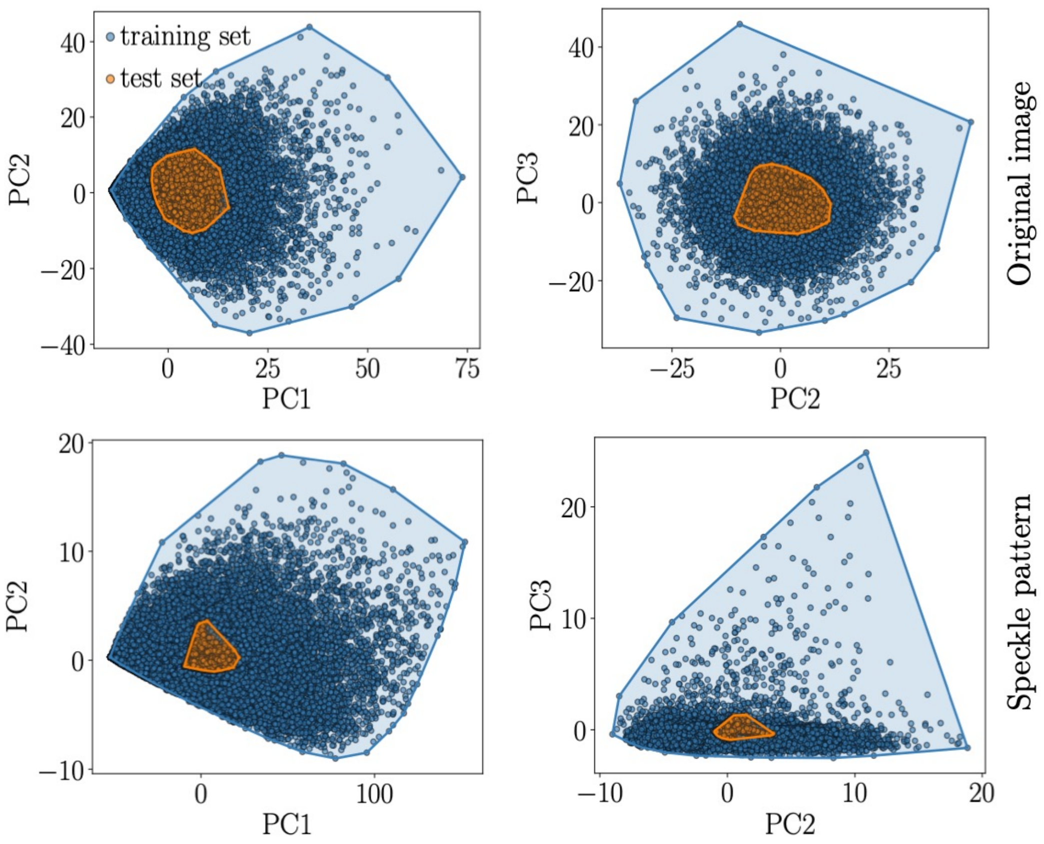
Proof of concept lab study: a laser illuminated DMD replays synthetic and measured beam images.

DMD (Digital Micromirror Device): a programmable array of microscopic mirrors used to display spatial light patterns.

Synthetic data - Stochastic Gaussian Mixture (SGM)

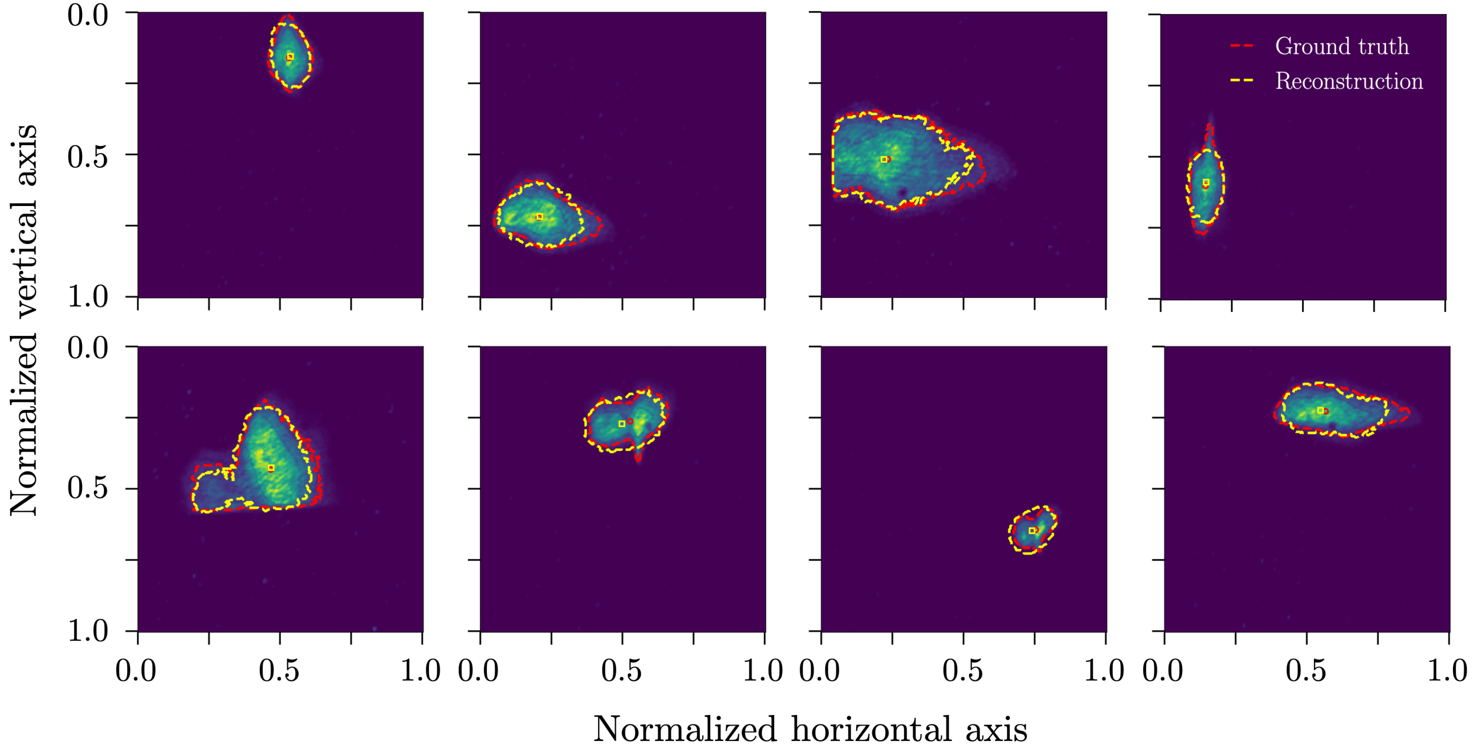


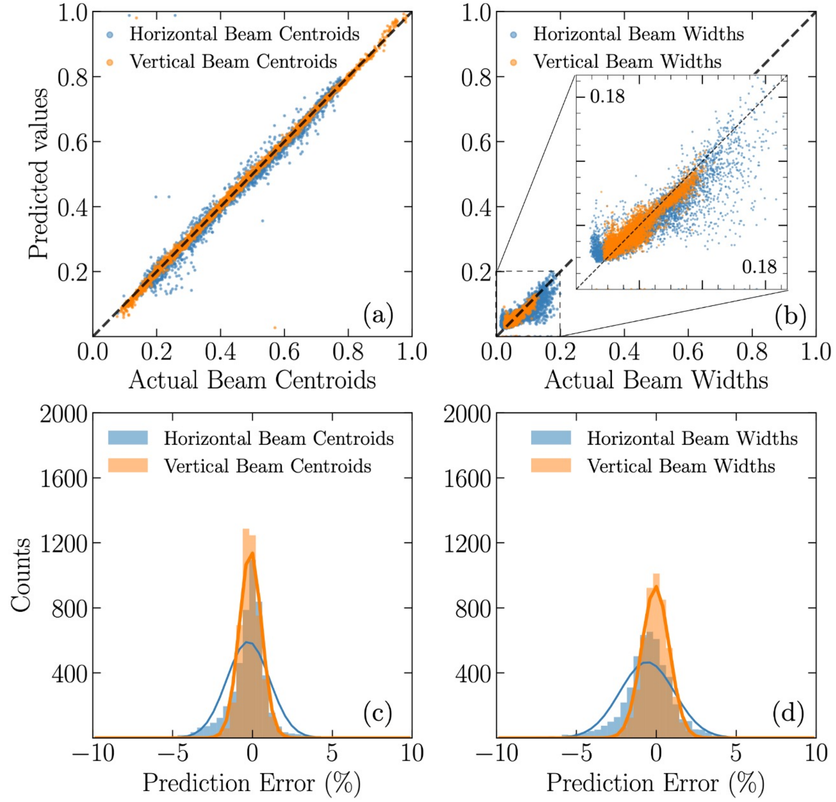
Example: three Gaussian components approximate a complex transverse beam profile



The synthetic data covers a broader region than the test beam data, indicating greater diversity and parameter space coverage.

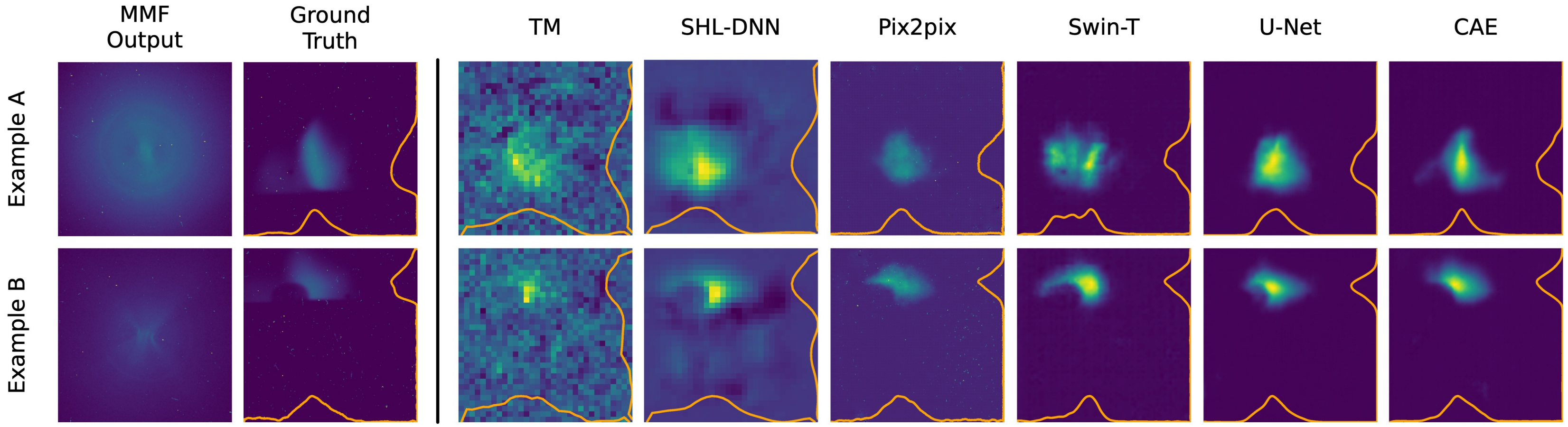
Reconstruction with SGM trained data



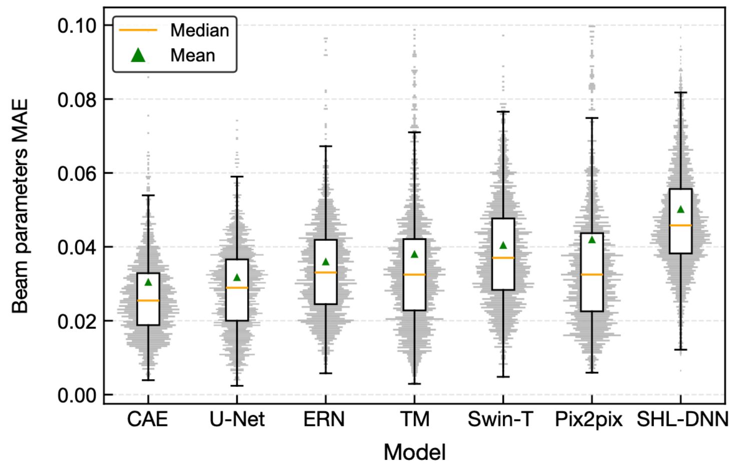


Trained **only on synthetic** SGM data, the model achieved a mean RMSE of **1.49%** on the DMD lab test set (replayed beam images), **77% lower** than the 6.59% baseline.

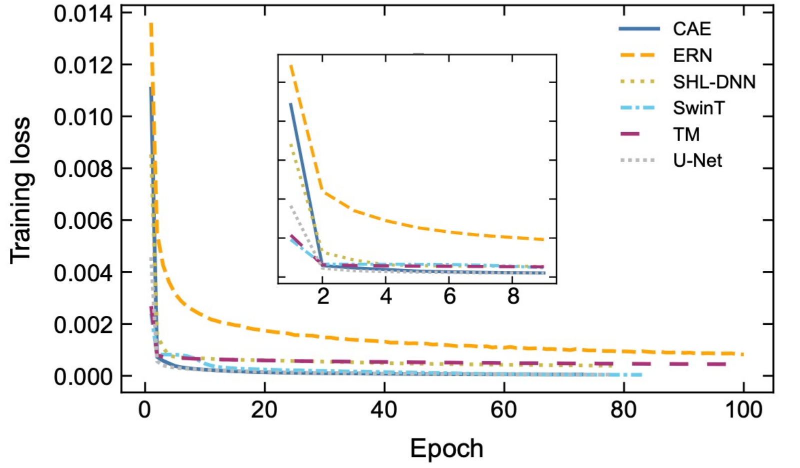
Which reconstruction model should we use?



Example reconstructions



Reconstruction error distribution

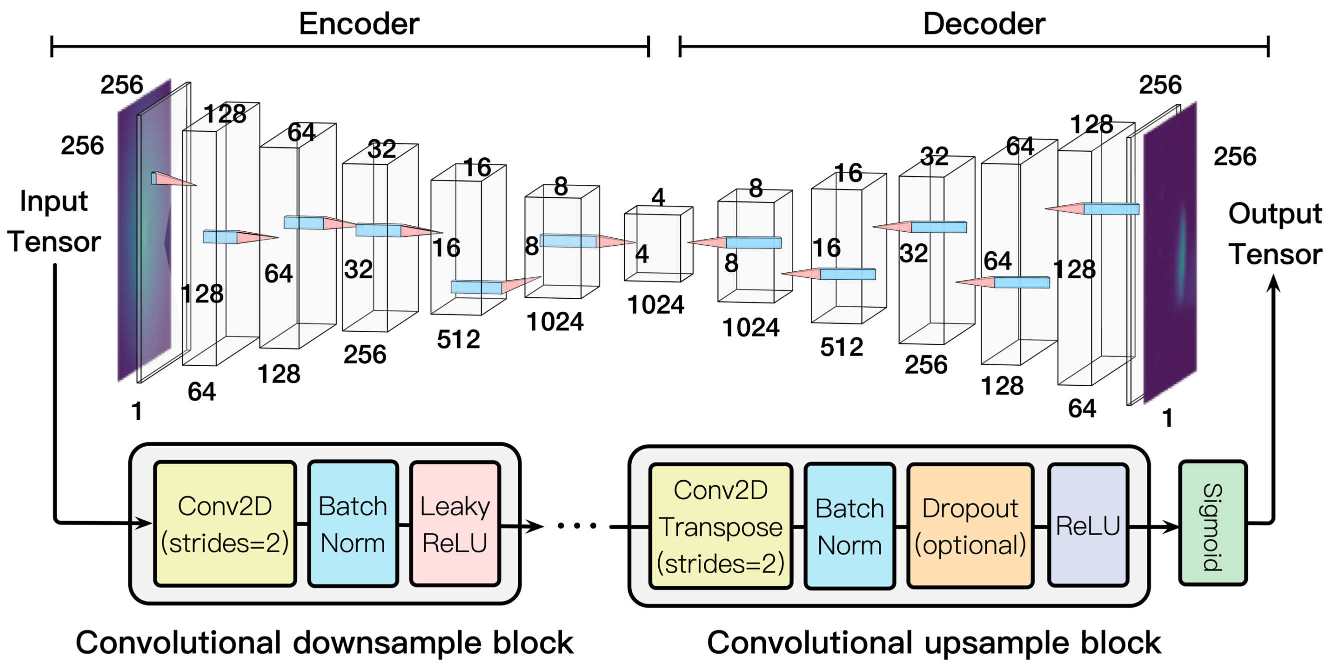


Convergence speed

Model	Size [MB]	Training Time [min]
SHL-DNN	80	17 ± 1
ERN	46	54 ± 25
CAE	71	59 ± 18
TM	256	61 ± 6
Swin-T	150	153 ± 31
Pix2pix	104	155 ± 89
U -Net	83	311 ± 13

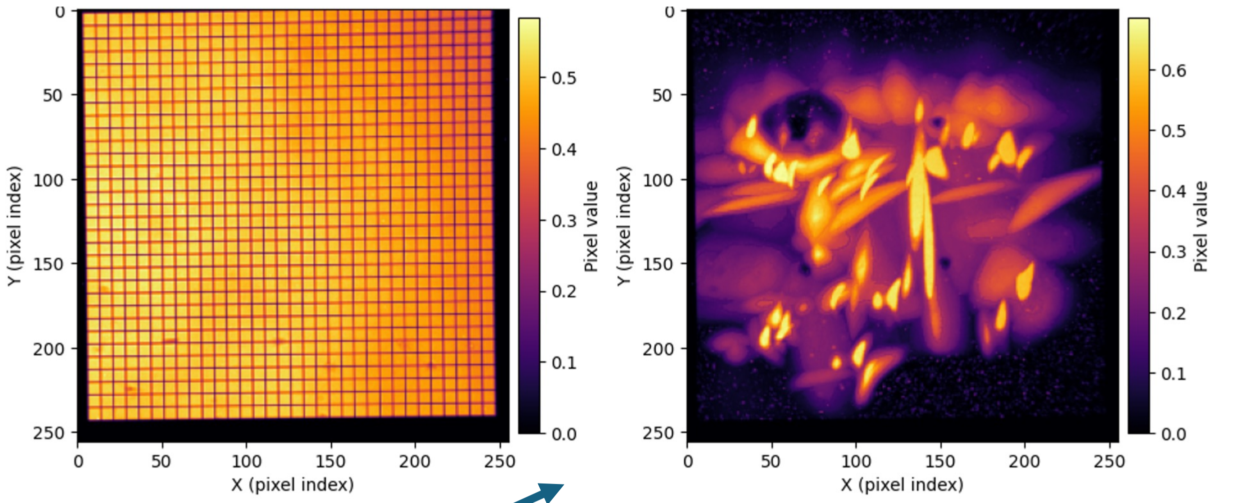
Computational cost

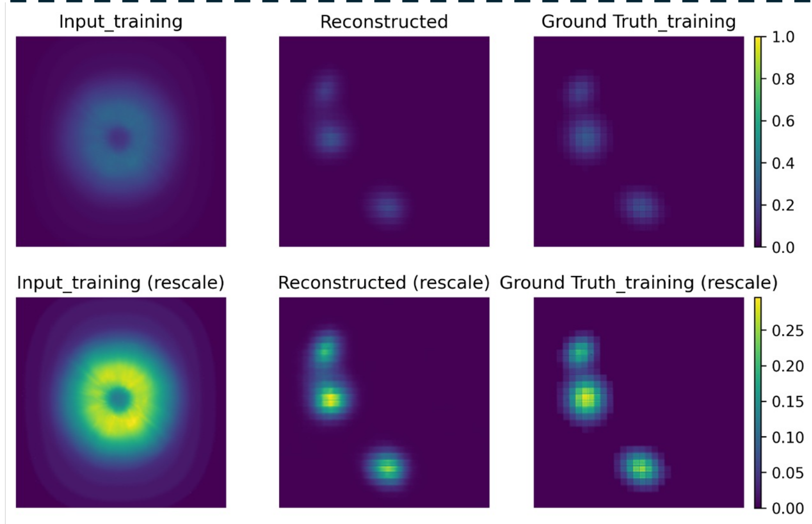
Convolutional autoencoder (CAE) for reconstruction



- **Encoder**: compresses the 256×256 MMF image into a compact 4×4×1024 latent representation.
- **Decoder**: reconstructs the transverse beam image from this latent representation.
- **Stride-2 convolutions**: learn the down sampling instead of using fixed heuristics.
- **No skip connections**: forces information through the bottleneck rather than directly copying low level features.

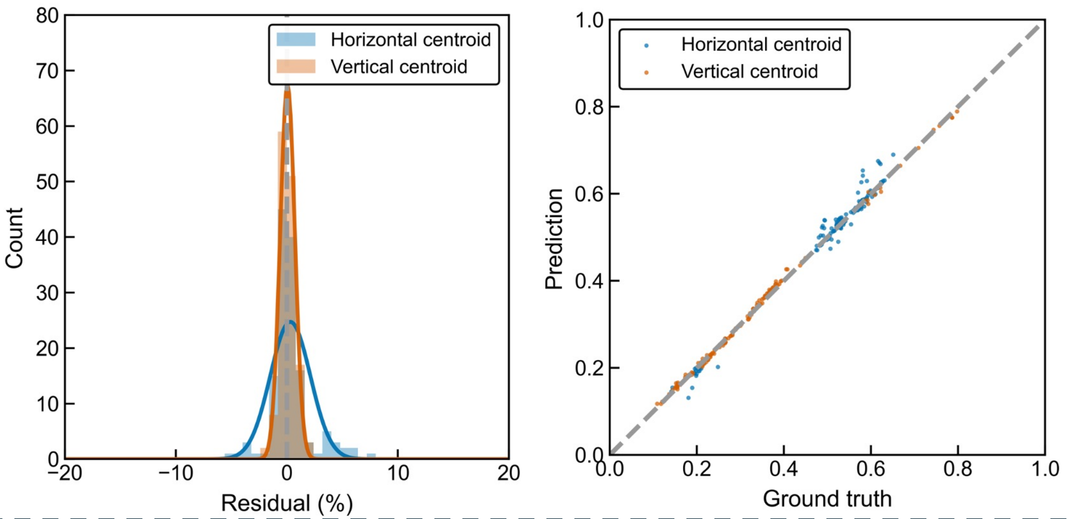
Can we train without beam data? Using a spatial response basis





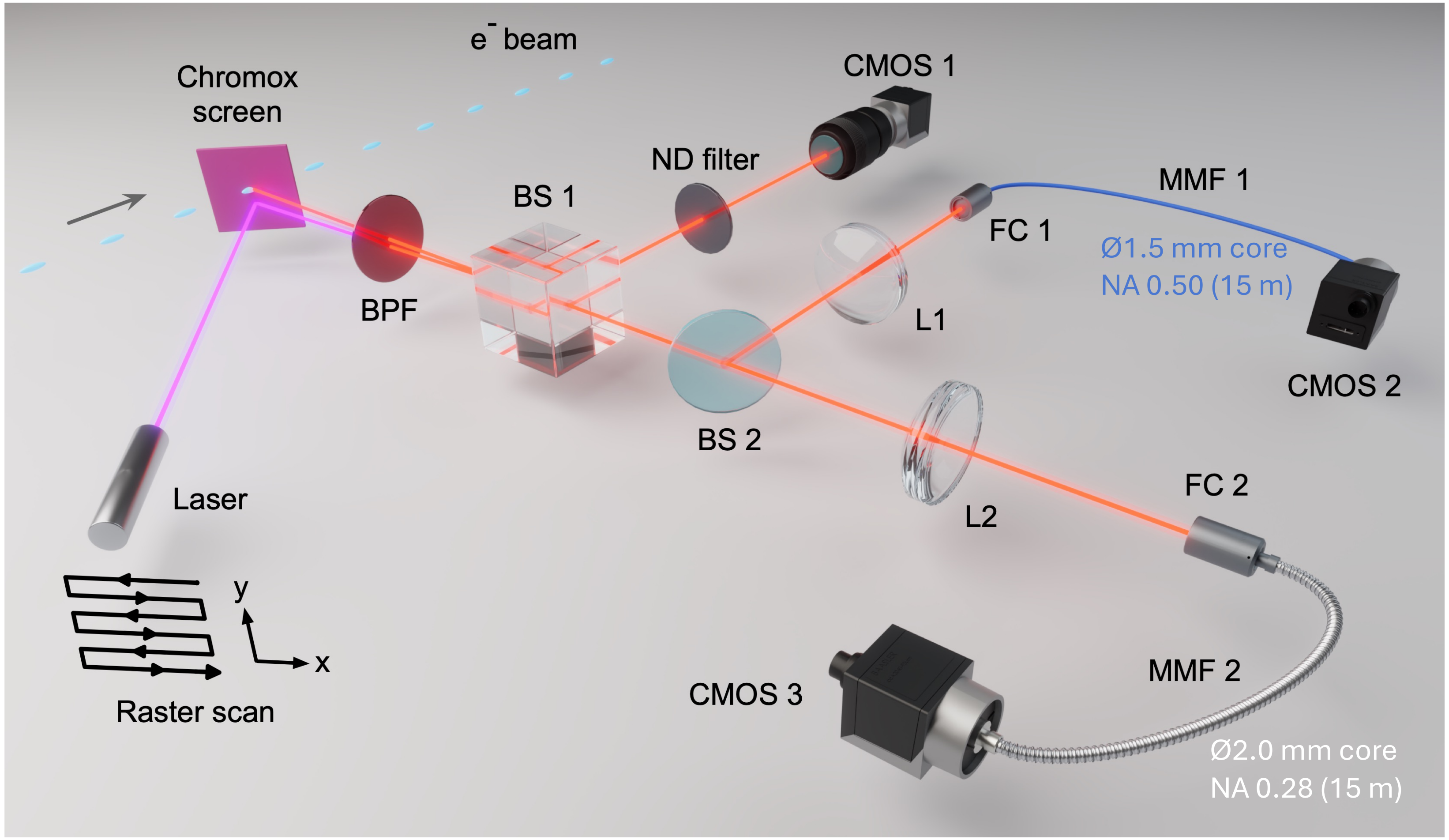
Proof of concept study: Sliding block patterns displayed on the DMD form a spatial response basis.

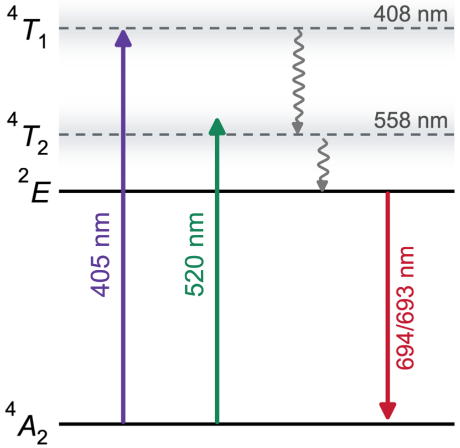
Previously measured beam images are also replayed on the DMD for validation.



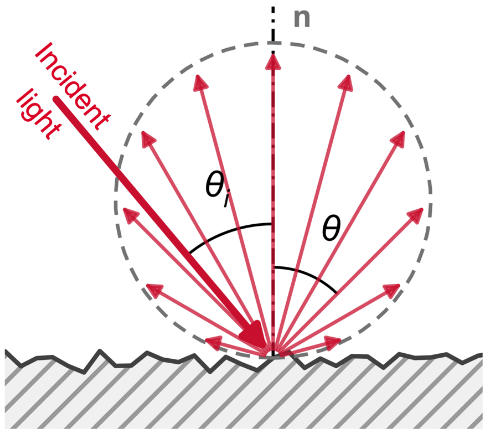
The measured spatial responses are linearly combined to generate synthetic training data. Then validated on beam image.

Cross-domain experimental setup at CLEAR





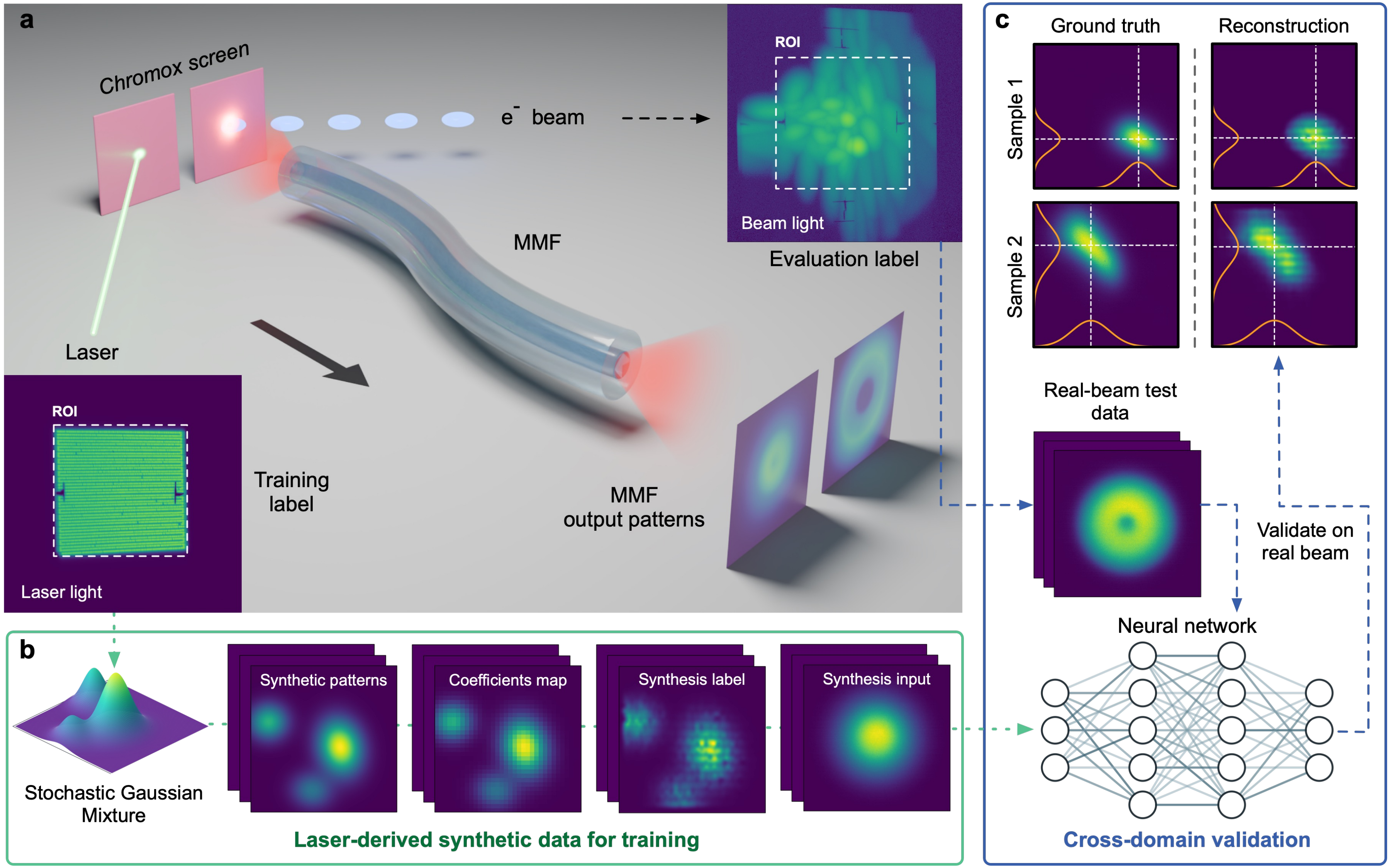
Laser-excited luminescence



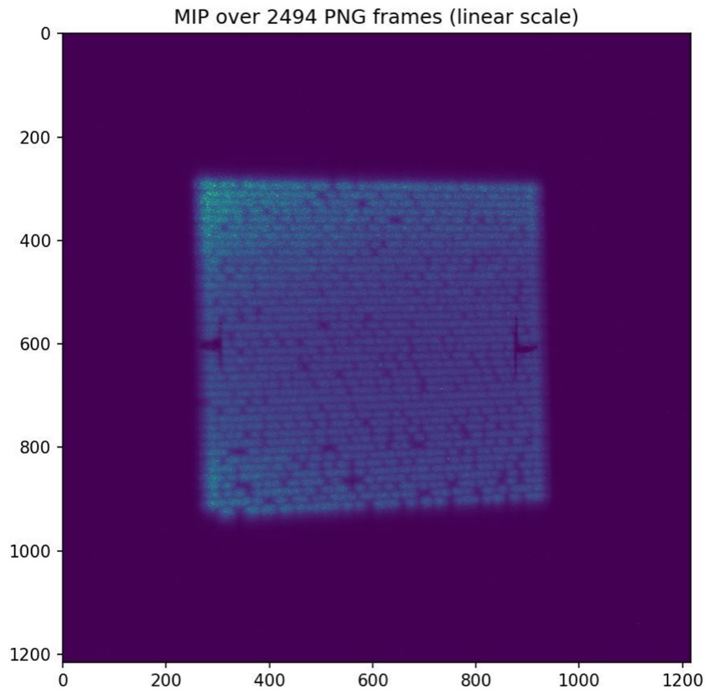
Diffuse reflection

Training data were collected using **two illumination modes** (excitation and reflection), with **two wavelengths per mode** and **two large core MMFs**, including one **radiation-resistant fiber (MMF 2).**

Laser-derived synthetic training

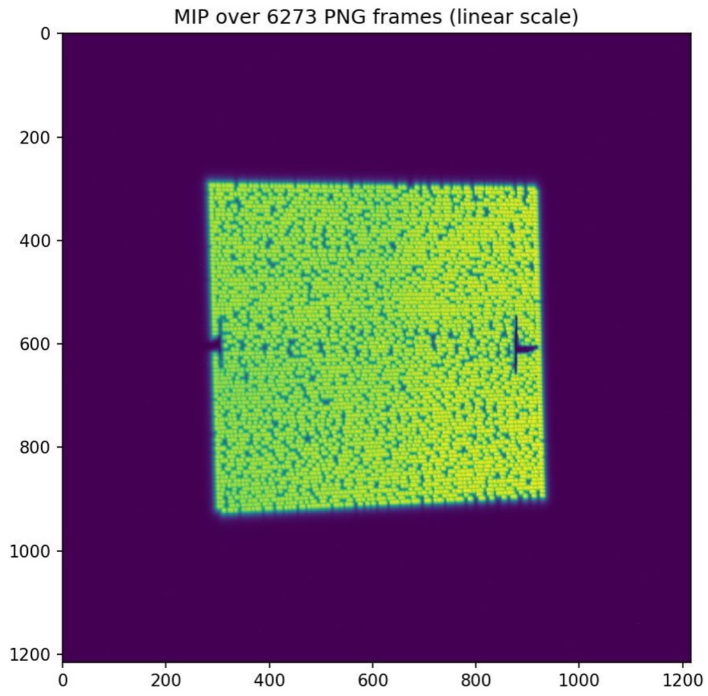


Basis scans at different spatial granularities



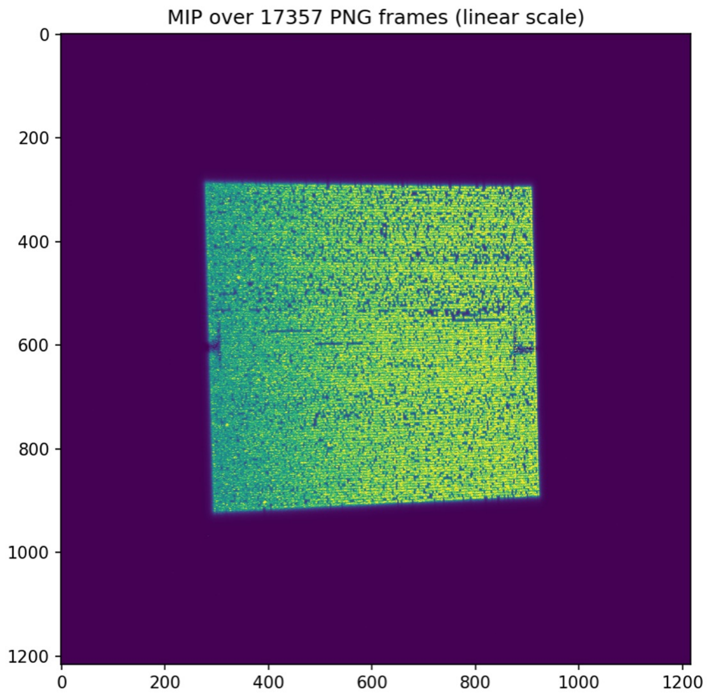
Laser excitation

(12 mins)



Laser excitation

(30 mins)

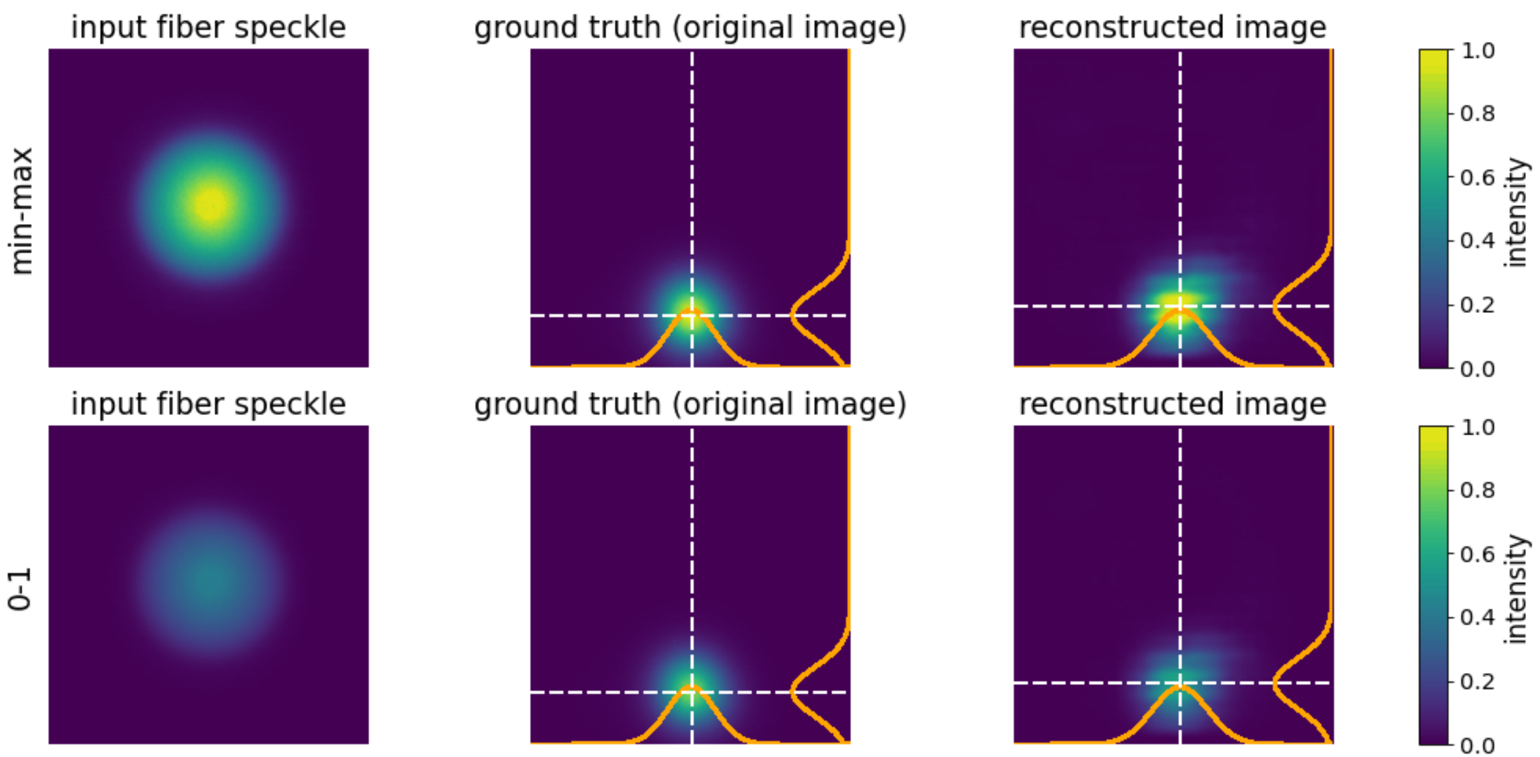


Laser reflection

(1h 20 mins)

- Scan density is a trade-off between **resolution**, **SNR**, and **scan time**.

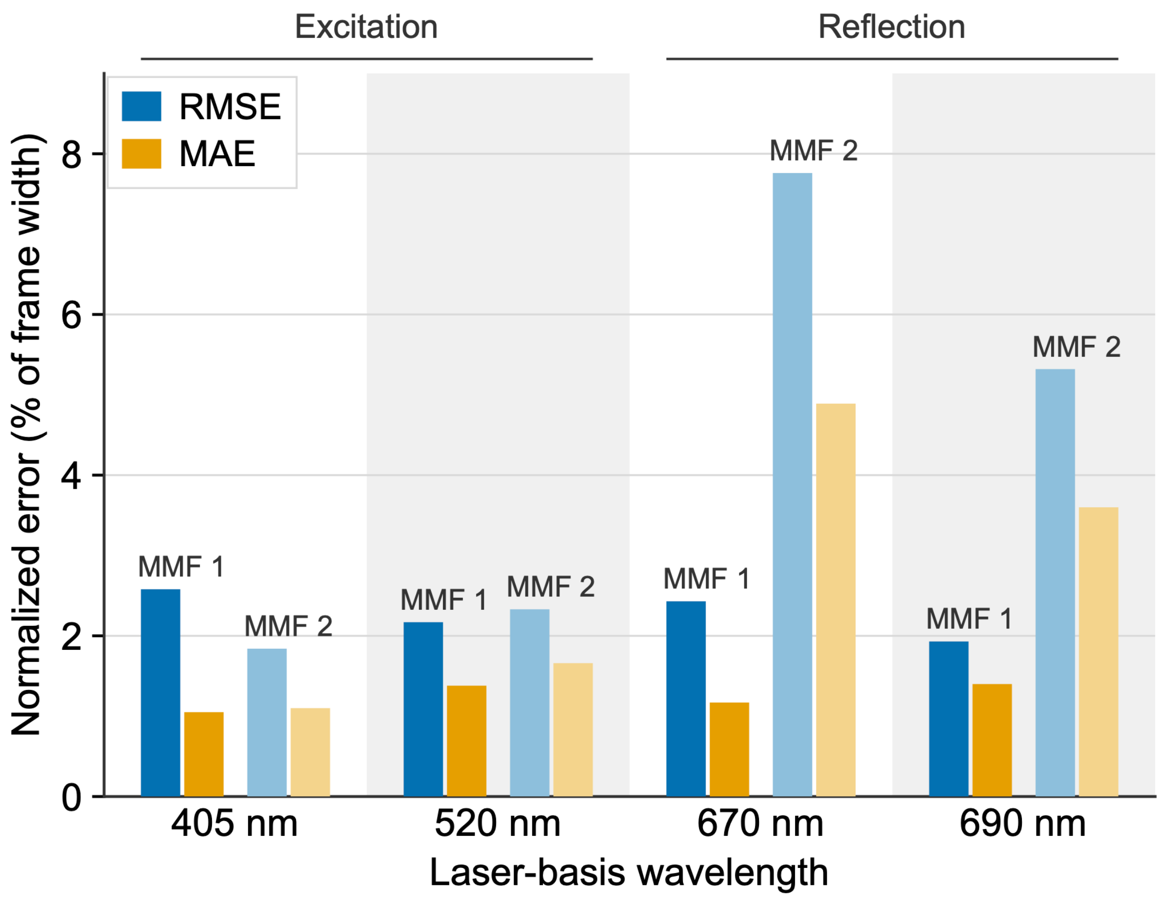
Preliminary cross-domain reconstruction examples



405 nm excitation; MMF 1 laser-derived basis with mixed training pipeline (beam-shape prior : SGM = 0.3 : 0.7)

- Training shape source comparison: SGM only: **RMSE 1.88%, MAE 1.30%** SGM + beam-shape prior: **RMSE 2.58%, MAE 1.05%** (Average normalized error over μ_x, μ_y, σ_x, σ_y)
- **Training patterns matter**: how the laser-derived basis is spatially combined affects reconstruction performance.

Preliminary beam test-set results



- Preliminary results provide a first comparison across four wavelengths and two fibers.
- Each wavelength uses an <u>independently acquired beam test set</u>, while the corresponding laser basis was acquired with <u>slightly different spot sizes</u>.
- All results use the same mixed training pipeline: laser-derived MMF basis, with <u>beam-shape priors</u> used only to generate part of the synthetic training data.

Future work

1. Quantify and optimize the calibration basis for **SNR** and **spatial resolution**.

2. Study **long-term** fiber **stability** and temporal drift.

3. Evaluate accumulated **radiation effects** on the MMF imaging system.

4. Reference-camera-free acquisition using motor position and a virtual input spot

Conclusion

1. Developed a tunable **SGM-based** generator for diverse, high coverage beam-like **synthetic training data**.

2. Compared reconstruction architectures and selected a compact **convolutional autoencoder** tailored to this task.

3. Preliminary **cross-domain** results show that laser-derived calibration can generate training data that **transfers** to real beam reconstruction.

Thank you