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ARTIFICIAL INTELLIGENCE-ASSISTED BEAM DISTRIBUTION IMAGING USING A SINGLE MULTIMODE FIBER AT CERN

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Abstract

In the framework of developing radiation tolerant imaging detectors for transverse beam diagnostics, the use of machine learning powered imaging using optical fibers is explored for the first time at CERN. This paper presents the pioneering work of using neural networks to reconstruct the scintillating screen beam image transported from a harsh radioactive environment over a single, large-core, multimode, optical fiber. Profiting from generative modeling used in image-to-image translation, conditional adversarial networks have been trained to translate the output plane of the fiber, imaged on a CMOS camera, into the beam image imprinted on the scintillating screen. Theoretical aspects, covering the development of the dataset via geometric optics simulations, modeling the image propagation in a simplified model of an optical fiber, and its use for training the network are discussed. Finally, the experimental setups, both in the laboratory and at the CLEAR facility at CERN, used to validate the technique and evaluate its potential are highlighted.

INTRODUCTION

The Beam TV observation system (BTV) is the most widely used devices for beam image observation at CERN [1]. It is an imaging system that collects the visible light emitted by the particle beam crossing a phosphor screen, or other radiator inserted in its path, inside the vacuum chamber. The optical system relays the beam distribution image imprinted on the screen through a viewport to a detector, often a camera. In harsh radioactive environments, in-house developed cameras based on VIDICON tubes are currently in use. With the production of the tubes being discontinued worldwide, image transportation through fibers is one of the options currently being investigated as a replacement at CERN [2].

In this framework, pioneering work to reconstruct the beam's transverse distribution using a single, large-core, multimode optical fiber began in 2020. It takes advantage of advances in generative modeling using deep learning methods, such as convolutional neural networks, and attempts to apply them to beam diagnostics. In this paper the possibility of converting back the patterns at the output of the multimode fiber imaged on a camera into beam distributions is explored and the performance of such a detector in measuring beam centroid and width is assessed. Finally an outlook for the future developments will be presented.

WORKING PRINCIPLE

The proposed solution is based on an "extended" optical system that is meant to replace the rad-hard detector. The scintillating screen light is collected and its image is relayed away from the radiation area where it can be acquired using a standard CMOS camera. The system logically is split in three parts:

- a first stage refractive system, imaging the beam screen and coupling the image into an optical fiber,
- a multimode large core fiber transporting the light away from the harsh radioactive environment,
- a final single stage optical system, relaying the exit of the optical fiber onto a CMOS camera placed in a lower dose area of the accelerator.

Optical Constraints

The first stage magnification is dictated by the chosen fiber core diameter and the field of view requested to cover the dynamics of the beam. A minimum magnification of 0.05 is needed for stage 1 in order to fit a typical working area of the screen (30 mm x 30 mm) onto the entrance of the multimode fiber *FP1500ERT* [3] with a core diameter of 1500 µm (used throughout the tests). Given its Numerical Aperture (NA) of 0.5, a typical light coupling efficiency of a few percent is to be expected. Finally, a 5x amplification is needed to relay the fiber output to a typical CMOS sensor (6.6 mm x 4.1 mm). In and out optical coupling are optimized using high NA microscope objective lenses. The pair of images obtained for the beam image and fiber output will be analyzed using machine learning algorithms.

PIX2PIX CGAN MODEL

The problem under discussion could be formulated as an "Image-to-Image" translation. A classical problem that is addressed with Generative Adversarial Networks (GAN) that consist of a generator and discriminator network that improve mutually in the adversarial evolution. The state-of-the-art framework for general purpose image translation is Pix2Pix [4], a "conditional" GAN since the generator model is provided with a target image and trained to both fool the discriminator model and to minimize the loss between the generated image and the expected target image. A slightly modified version of the Pix2Pix network is used in this study:

Generator U-Net

The U-Net [5] model architecture is very similar to autoencoders, as it involves downsampling to a bottleneck and upsampling again to an output image, but links or skip-connections are made between layers of the same size in the encoder and the decoder, allowing the bottleneck to be circumvented. For our application, the input image is passed in 6 consecutive convolutional layers of size 64, 128, 128,

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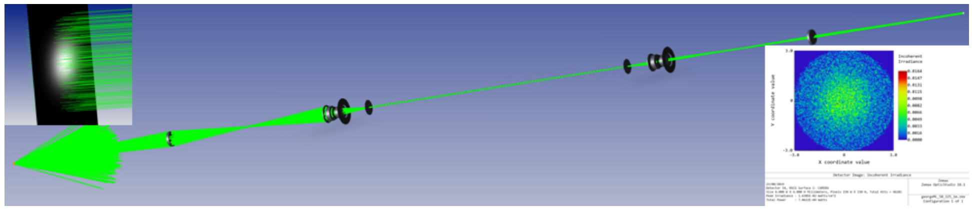

Figure 1: The full 3 stage optical system simulated in Zemax Optic studio in non sequential ray tracing mode.

256, 512 and 512 with batch normalization, dropout, and activation layers at each level. Only a single skip connection is used at the top level. The loss function for the generator training was also expanded to include the Euclidean norm (L2) on both the horizontal and vertical projections of the target and input images.

Discriminator

The PatchGAN discriminator model is implemented as a deep convolutional neural network, where the effective receptive field of each output of the network maps to a specific size in the input image. The output of the network is a single feature map of real/fake predictions that can be averaged to give a single score. The original Pix2Pix patch size of 70×70 is used and demonstrated to be effective also for our case.

MODEL APPLICATION

The feasibility of this technique was probed at the theoretical level with simulations and then experimentally in setups both in the laboratory and in the accelerator, as summarized in this section.

Optical Simulations

A realistic dataset was developped in Zemax OpticStudio [6]. Non-sequential ray tracing mode was used, accounting for ray split, scattering, and back reflections, as shown in Fig. 1. The fiber was simulated with straight concentric cylinders with the refractive index provided by the manufacturer at 589.3 nm. Using the interactive extension ZOS-API, the optical system was coupled to a python script controlling the incoming rays source (system illumination). 2D Gaussian illuminations were randomly generated emulating different beam conditions impinging on the BTV screen. A dataset of 1000 image pairs: input image and propagated rays image in Zemax to the simulated CMOS detector was created.

The ML model was successfully trained on a subset of 300 image pairs, after 100 epochs with Adam optimizer learning rate of 2e-4 for both the generator and the discriminator. Tested on the remaining 700 pairs, the reconstruction error of both the beam width and position was bound by an rms error ≤ 2%. Figure 2 shows qualitatively a few reconstructed samples.

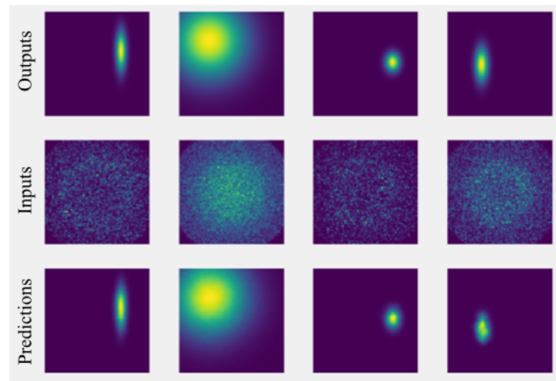

Figure 2: Predicted samples (lower row) applying the trained network on simulated model inputs, at the fiber exit (central row), compared to truth distributions at the fiber entrance (upper row).

Laboratory Installation

The encouraging simulations results, motivated the purchase of the large core fiber and dedicating a laboratory measurement setup to assess the feasibility of the image transmission in a real fiber, studying the coupling efficiency the focal length and numerical apertures of the optical system. For an increased robustness and to ease the setup, the final imaging stage relaying the fiber exit to the CMOS was replaced by a mechanical fixing (SMA connectors) that rigidly ties the fiber end to the camera with a few mm distance ensuring most of the emitted light is collected on the sensor. In addition to the laser alignment line, a portable LED screen controlled via a python script was used to display varying 2D multivariate normal distributions in position and width acting as the source illumination emulating the BTV screen. Coupling efficiencies around 10% were obtained and a dataset of ~5000 collected, that allowed training a model featuring a reconstruction error ≤ 10% rms on width in both planes.

CLEAR Facility Experiment

The CERN Linear Electron Accelerator for Research (CLEAR) is a Linac producing bunched electron beams accelerated up to 220 MeV. A table-top setup with our fiber installation was prepared, pre-aligned and installed in parallel to one of the operational BTV in its experimental beam line. A pellicle beam-splitter was introduced in the BTV optical path to share the light emitted by the Chromox ($Al_2O_3 : CrO_2$) screen. The location was chosen next to the

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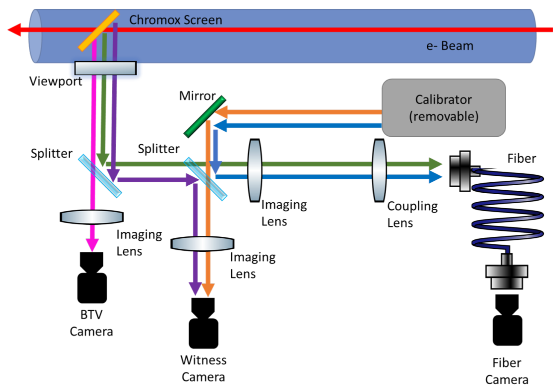

Figure 3: Sketched layout of the experimental setup installed at CLEAR showing the fiber installation with its calibration line in parallel to the operational BTV.

focusing triplet before the plasma cell, where by changing the strength of quadrupoles QFD760, QDD765 and QFD770, various beam distribution could be obtained on the screen. A slight trajectory misalignment was also introduced in the triplet to allow the beam centroid to be scanned on the scintillating screen in combination with the varying beam width. The installation sketched in Fig. 3 denotes with different colors the three light paths: in pink the operational BTV light path, in orange the calibration line light path, in green the image transport in fiber light path. A three hours dedicated beam Run took place in July 2020, using a 150 MeV electron beam where 1300 random beam distributions (highly non Gaussian) were obtained with the triplet scan. Using the

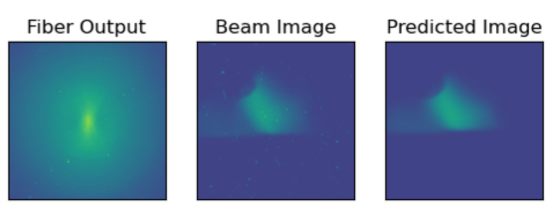

Figure 4: Typical beam image reconstruction for a model trained on real data. Note the non-Gaussianity of the obtained beam distributions with the triplet scan technique.

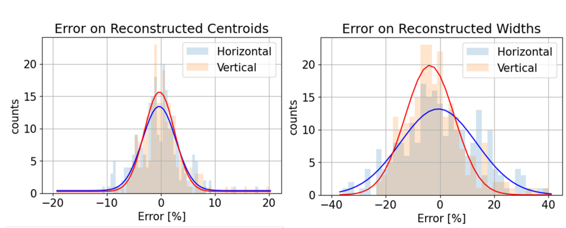

Figure 5: Errors distributions for the estimated beam centroid and width with the Pix2Pix trained on beam data.

pre-trained model on the calibrator screen dataset did not allow the reconstruction of the measured beam distributions. Despite the beam centroid being estimated with errors of ~ 15%, errors ≥ 50% on the width estimation were obtained. Therefore, a new training was carried out using beam data (300 samples) and then applied on rest of the dataset as depicted in Fig. 4. Figure 5 shows how the obtained model correctly estimated the centroids with an rms error of ~ 3% and width of ~ 14% and ~ 9% in the horizontal and vertical plane respectively.

OUTLOOK

To rule out the effect of transporting the optical system and its installation at CLEAR, by introducing mechanical deviations or vibrations invalidating the trained model, a new dataset was collected in-situ with the calibration system. The model was re-trained against the latter and tested on the beam dataset. Unfortunately, its predictive capabilities still did not improve.

Two main factors could be at the origin of the non-applicability of the pre-trained models: the ”Gaussian” distribution used in the training dataset that deviates greatly from the various beam distributions obtained with the triplets scan technique and the wavelength dependency of the fiber transmission that features an increase of attenuation by factor 4 between the narrow band emission of the Chromox screen at 693 nm and the calibrator LED screen emission range 450 nm-620 nm.

Future steps will focus on improving the calibration system to emulate better the screen light emission characteristics and investigating new transfer learning techniques that would allow reducing the size of the training dataset, thus reducing the dedicated beam time required.

CONCLUSION

An experimental demonstration for beam image transport in a large core multimode fiber was presented in this paper. The Pix2Pix conditional generative adversarial network was successfully used to reconstruct beam centroid and beam width with a standard error in the order of 10%. The trained model accuracy was proven in simulations, a laboratory setup and in the CLEAR facility with electron beams. The training transferability was not demonstrated since each of the three aforementioned scenarios required a re-training on its proper dataset. Future studies will focus on enriching the model with environmental factors (temperature and vibration levels) to increase its robustness and fidelity. Transfer learning techniques to reduce the training datasets size will also be investigated. Finally, as an alternative to cGANs, variational auto-encoders will be explored, since granting access to the latent dimension at the encoder bottleneck could allow a better control of the model parameters.

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REFERENCES

[1] S. Burger, E. Bravin, G. Ferioli, G. J. Focker, A. Guerrero Ollacarizqueta, and R. Maccaferri, "A New TV Beam Observation System for CERN", in *Proc. DIPAC'05*, Lyon, France, Jun. 2005, paper POT030, pp. 214–216.

[2] D. Celeste, E. Bravin, S. Burger, and F. Roncarolo, "Development and Test of a Beam Imaging System Based on Radiation Tolerant Optical Fiber Bundles", in *Proc. IPAC'19*, Melbourne, Australia, May 2019, pp. 2658–2660. doi:10.18429/JACoW-IPAC2019-WEPGW078

[3] Thorlabs, https://www.thorlabs.com/thorproduct.cfm?partnumber=FP1500ERT

[4] P. Isola *et al.*,"Image-to-Image Translation with Conditional Adversarial Networks", in *Proc. of the 2017 IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*, 2017, pp. 5967-5976. doi:10.1109/CVPR.2017.632

[5] O. Ronneberger *et al.*, "U-Net: Convolutional Networks for Biomedical Image Segmentation", in *Proc. of Medical Image Computing and Computer-Assisted Intervention – MICCAI 2015*, 2015, pp. 234-241. doi:10.1007/978-3-319-24574-4_28

[6] OpticStudio Zemax, https://www.zemax.com/pages/opticstudio