Towards Machine-learning Integrated Optoelectronic Computing Chips for Proton Radiography

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Abstract: We present a photonic convolutional neural network for proton radiography image enhancement that outperforms traditional techniques at reducing blur from sources such as multiple Coulomb scattering. We explore using edge-based optical computing in radiation environments. (LA-UR-25-30382)

1. Introduction

Proton radiography (pRad) is a powerful diagnostic tool that provides insights into material composition, density, and structure [1]. The pRad facility at the Los Alamos Neutron Science Center (LANSCE) uses a 800 MeV proton beam to diagnose high-speed dynamic experiments such powder gun experiments and pulsed-power implosions. Similar but different to conventional X-ray radiography, which uses photon attenuation as the basis for imaging, pRad relies on proton attenuation through the unique interactions of protons with the atomic nuclei of matter. The proton energy is attenuated by sources including but not limited to multiple Coulomb scattering, energy straggling, and nuclear interactions [1, 2]. However, these proton interactions are sources of significant image blurring that degrade the spatial resolution of pRad imaging. In this work, we present a deep learning image framework for pRad image deblurring at the Los Alamos National Laboratory (LANL). In addition, we will deploy this framework onto our chip-based optical neural network using foundry-based silicon photonic chips, a promising *radiation-hard* computation platform for edge computing in harsh radiation environments [3, 4].

2. Deep Learning for pRad Image Deblurring

Experimental pRad images are generated by detecting and capturing the remaining protons at the camera location. The captured image quality is degraded by image blur from sources such as multiple Coulomb scatter, chromatic abberation and detector blur. These blur sources can be classified into dependent and independent blur, where the dependent blurs change with proton energy, scattering angle, and material composition. This results in a complex, spatially-varying blur kernel that traditional image deblurring methods, such as the Wiener Filter and Richardson-Lucy, are unable to capture. To address this issue, we propose to design a deep learning deblurring algorithm for pRad image deblurring using a modified U-Net architecture [5]. While U-Net is popularly used for image segmentation, it has been increasing used for image deblurring tasks [6]. The network will take as input, the blurred image as well as the focus energy and output the reconstructed sharp image. We will refer to our framework as RadNet and its optical neural network implementation as ORadNet.

3. Results and Future Work

We use our forward model to generate a synthetic dataset consisting of 5,000 image pairs of blurry and ground-truth sharp images of size 1000×1000 pixels. The dataset consists of three different objects that are imaged at different focus energies, image locations, and rotations. The dataset is split into 70% training, 20% validation, and 10% testing. Figure 1b and c shows an example blurry and sharp radiographic image of a spherical object simulated at a focus energy of 22.2 MeV. The image is zoomed in to better show the blurring or liming effect at the object edge.

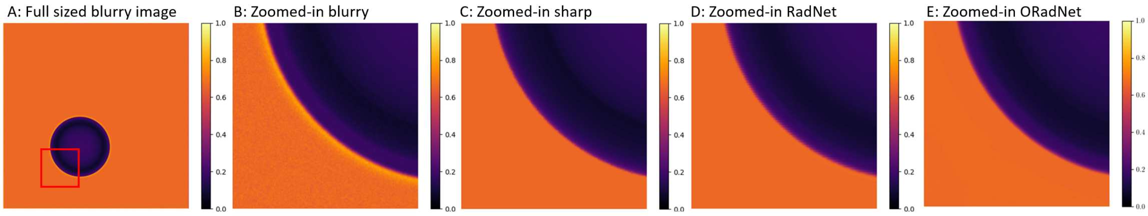

Fig. 1: Visual comparison of an example radiographic image of a spherical object. Our proposed method (d) and (e) removes the liming effect around the object edge and the background noise.

The key electronic network training parameters are set to 85 training epochs, a batch size of 8, a learning rate of 0.001 using the Adam optimizer, and a scheduler with a factor of 0.5 and a patience of 5. The key optical network training parameters are set to 59 training epochs, a batch size of 6, a learning rate of 0.001 using the Adam optimizer, and scheduler with a factor of 0.5 and patience of 10. The network is trained on a NVIDIA RTX A3000 laptop GPU. We evaluate trained model performance using the peak signal-to-noise ratio (PSNR), structural similarity index measure (SSIM), and the mean squared error (MSE) metrics. The model performance is summarized in Table 1. Our RadNet and ORadNet outperforms traditional deblurring techniques in all error metrics. Figure 1d and 1e shows the reconstructed sharp image by RadNet and ORadNet, respectively, where the liming around the object is clearly removed.

Table 1: Summary of pRad image deblurring performance on the test dataset. The reported numbers are given as the mean $\pm$ standard deviation.

Method	**PSNR**	**SSIM**	**MSE**
Benchmark	32.15 ± 1.65	0.789 ± 0.002	$63e-5 \pm 3.38e-8$
Wiener Filter	33.14 ± 4.08	0.880 ± 0.004	$54e-5 \pm 6.33e-8$
RadNet	47.40 ± 1.04	$0.998 \pm 6.85e-7$	$1.88e-5 \pm 3.08e-11$
ORadNet	46.61 ± 0.99	$0.997 \pm 1.08e-6$	$2.24e-5 \pm 3.18e-11$

Currently, we have demonstrated the performance of both the electronic and chip-based optical neural network versions of our pRad image deblurring method using a modified U-Net. Further work is being done to improve the internal object deblurring performance. In addition, more work is being done in parallel to test other object shapes, material compositions, and dynamic movies. In summary, this work is an initial building block towards a broad pRad image enhancement tool using deep learning and integrated edge deployment.

References

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