Sub-micron Ultracold Neutron Position Resolution using Chip Based Optical Neural Network

S. Lin,[1,2] H. Zhu,[2] S. Clayton,[1] C. L. Morris,[1] Z. Tang, [1] Z. Wang,[1,*] and R. T. Chen[2,3,4,*]

[1] *Los Alamos National Laboratory, Los Alamos, NM 87545, USA*
[2] *Department of Electrical and Computer Engineering, The University of Texas at Austin, Austin , TX 78705, USA*
[3] *Microelectronics Research Center, The University of Texas at Austin, Austin , TX 78758, USA*
[4] *Omega Optics, Inc., Austin , TX 78757, USA*
[*] *Z. W. (zwang@lanl.gov), R. T. C. (chenrt@austin.utexas.edu)*

Abstract: High spatial resolution of ultracold neutron (UCN) measurements of 1 μm or less is highly desired for many UCN experiments. Optical neural networks are potential radiation-hard hardware platforms for real-time, energy-efficient analysis of UCN hits. (LA-UR-23-33103)

1. Introduction

Ultracold neutrons (UCNs) have a kinetic energy less than 400 neV and are the coldest free neutrons produced in laboratories with UCN production facilities. With their unique properties, UCNs are a powerful tool to study to the fundamental forces in nature and are utilized in many experiments such as neutron lifetime measurement, neutron beta decay, and neutron electric dipole moment. In recent years, new UCN experiments such as the studies of UCN quantum states and gravity benefit from precise UCN position-sensitive measurements where a spatial resolution of 1 μm or less, comparable to the UCN wavelengths of ~ 100 nm, is highly desired. Our recent work [1] demonstrated sub-micron position resolution for UCN detection using a room-temperature complementary metal oxide semiconductor (CMOS) image sensor and a fully connected neural network (FCNN). However, obtaining real-time UCN hit positions is highly desired and will enable advancements for future UCN quantum science and technology.

For real-time deep learning, or deep-learning at the edge, there are electronic-based embedded platforms for AI developed by the hardware industry. These devices can be used to deploy a trained neural network for real-time analysis on edge devices (i.e. CMOS image sensor). However, UCN experiments and in broader nuclear imaging experiments such as X-ray and proton radiography will subject the electronic hardware to radiation environments, which results in radiation damage and noise. Meanwhile, optical neural networks (ONNs) are potentially radiation-hard, while out performing electronic-based platforms in energy efficiency for high-speed and parallel computing [2].

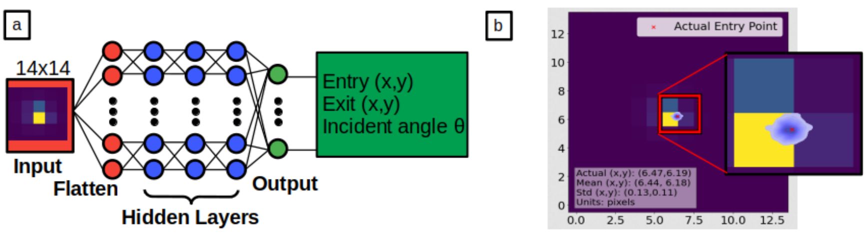

Fig. 1: (a) Overview of FCNN architecture which takes as input a UCN hit image and outputs the entry and exit position in (x,y) as well as the incident angle θ. (b) An example prediction by the FCNN on the entry point as a kernel density plot.

Accepted in CLEO 2024

2. Deep Learning for UCN Position Resolution

It is necessary to generate a synthetic dataset consisting of experiment-like UCN hit images and their corresponding ground-truth hit position as this information is not available from the experimental images. We leverage Allpix Squared [3], an open-source silicon detector simulation tool that implements end-to-end Monte Carlo simulations, to generate synthetic UCN hit images and their corresponding ground-truth hit positions. An example image is shown in Figure 1. In [1], we show that the synthetic UCN hit images and energy distribution are very similar to the experimental data. We use a FCNN to model the underlying detector physics by learning a mapping from input UCN hit image to the output ground-truth labels consisting of the entry and exit coordinate as well as the incident angle. An overview of the FCNN architecture is shown in Figure 1(a).

3. Results and Discussion

We use Allpix Squared to generate a synthetic dataset consisting of approximately 50,000 UCN hit images and their corresponding ground-truth labels. The dataset is split into 60% for training, 20% for validation, and 20% for testing. During the testing phase, the dropout layers in the FCNN are enabled to allow for uncertainty quantification by feeding each input image into the trained network 500 times to simulate Monte Carlo runs. Figure 1(b) shows and example entry (x, y) prediction as a blue kernel density plot for one synthetic hit image.

Table 1 summarizes the overall prediction performance of the trained FCNN and the trained optical subspace neural network (OSNN) [4] implementation of the FCNN. Although the OSNN is less accurate than the FCNN, it still achieves the desired sub-micron position resolution desired for position sensitive UCN measurements. For this CMOS camera, 1 pixel = 1.67 µ, and thus the OSNN achieves a maximum mean absolute error of 0.1991 pixels (0.33 µm) for position resolution.

Further work and algorithm development is needed for edge deployment and real-time implementation. Currently, the position resolution algorithm is designed to take in post-processed UCN hit images as input, where the size 14×14 images are extracted from the full dimension of the CMOS camera (i.e. 10 megapixels). In summary, an object detection algorithm is required to identify and extract the UCN hits and the position resolution algorithm needs to be adapted to determine the UCN hit position of the full CMOS camera.

Table 1: Summary of FCNN and OSNN performance on the test dataset. The mean absolute error (MAE) and the mean absolute percent error (MAPE) for each output label is computed. Note that 1 pixel = 1.67 µm.

		Entry x (pixels)	**Entry y (pixels)**	**Exit x (pixels)**	**Exit y (pixels)**	**θ (degrees)**
FCNN	**MAE**	0.1255	0.1286	0.1750	0.1777	4.485
	MAPE	1.995%	1.948%	2.808%	2.663%	16.899%
OSNN	**MAE**	0.1611	0.1552	0.1991	0.1965	5.085
	MAPE	2.568%	2.341%	3.178%	2.955%	21.263%

References

1. S. Lin, J. Baldwin, M. Blatnik, S. Clayton, C. Cude-Woods, S. Currie, B. Filippone, E. Fries, P. Geltenbort, A. Holley, W. Li, C.-Y. Liu, M. Makela, C. Morris, R. Musedinovic, C. O'Shaughnessy, R. Pattie, D. Salvat, A. Saunders, E. Sharapov, M. Singh, X. Sun, Z. Tang, W. Uhrich, W. Wei, B. Wolfe, A. Young, and Z. Wang, "Demonstration of sub-micron ucn position resolution using room-temperature cmos sensor," Nucl. Instruments Methods Phys. Res. Sect. A: Accel. Spectrometers, Detect. Assoc. Equip. **1057**, 168769 (2023).
2. S. Lin, S. Ning, H. Zhu, T. Zhou, C. Morris, S. Clayton, M. Cherukara, R. Chen, and Z. Wang, "Neural network methods for radiation detectors and imaging," arXiv preprint arXiv:2311.05726 (2023).
3. S. Spannagel, K. Wolters, D. Hynds, N. A. Tehrani, M. Benoit, D. Dannheim, N. Gauvin, A. Nürnberg, P. Schütze, and M. Vicente, "Allpix2: A modular simulation framework for silicon detectors," Nucl. Instruments Methods Phys. Res. Sect. A: Accel. Spectrometers, Detect. Assoc. Equip. **901**, 164–172 (2018).
4. C. Feng, J. Gu, H. Zhu, Z. Ying, Z. Zhao, D. Z. Pan, and R. T. Chen, "A compact butterfly-style silicon photonic–electronic neural chip for hardware-efficient deep learning," Acs Photonics **9**, 3906–3916 (2022).

Accepted in CLEO 2024