Neural-net-based imager offset estimation in fieldable associated particle imaging

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Introduction

Focus Areas: Radiation Detection | Nuclear Engineering
Crosscutting Areas: Modeling and simulation
Neutron Imaging

- Complements X-ray imaging
- Nuclear interactions mean it can resolve isotopic differences
- Common shielding materials that are effective at attenuating X-rays do not interact as readily with neutrons

Image credit: Seth McConchie, ORNL
Associated Particle Imaging

• Method to improve signal to noise by filtering in time domain

• Three modes:
  – Transmission imaging
  – Scatter imaging
  – Fission imaging

• ORNL Nuclear Materials Identification System (NMIS) uses deuterium-tritium generator to produce $\alpha$ (3.54 MeV) and neutron (14 MeV) in opposite directions

Example neutron radiograph with 2D pixelated detector. Scale is the attenuation coefficient in the material.

Image credits: Seth McConchie and Matthew Blackston, ORNL
Problem statement

In a fully portable, fielded version of NMIS, the neutron detector array could be misaligned relative to its nominal position. This affects both scatter rejection and image reconstruction.

Solution: design a neural network to infer the position of a neutron array (distance, offset, and rotation) from measurement data.
Approach

- Simulate neutron physics with Monte Carlo (MCNP)
- Use measured data to incorporate detector response
- Train neural network on generated data
Monte Carlo (MCNP) Workspace

- No line of sight assumed between source and detector due to steel box
- Annulus materials selected from plastic, steel, aluminum, tungsten, DU, or explosive
- MCNP source distribution based on curves fit to measured data from generator → separate “source” for each alpha pixel matching correlated emission cone
- Neutron pixels: PVT, 1” x 1” x 4” based on existing NMIS design
- Train / Test: 842 / 157 simulations

<table>
<thead>
<tr>
<th></th>
<th>$\Delta X$ (cm)</th>
<th>$\Delta Y$ (cm)</th>
<th>$\Delta \Theta$ (°)</th>
<th>Outer radius (cm)</th>
<th>Inner radius (cm)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Min</td>
<td>-15</td>
<td>-15</td>
<td>-7.5</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>Max</td>
<td>15</td>
<td>15</td>
<td>7.5</td>
<td>25</td>
<td>24.35</td>
</tr>
</tbody>
</table>
Accounting for detector timing response

- MCNP does not model light/charge collection in neutron/alpha detectors
- Timing is assigned using constant fraction discriminators (CFD)
- Measured 1000 pulses per channel and simulated CFD to find timing variability
- Created approximated distribution alpha times-> combined with MCNP simulations of alpha to blur measurements
Important features in common:

- Each blur represents one alpha detector in coincidence with 3-5 neutron pixels
- Intensity (number of counts) matches to within range defined by generator power
- Length of blur matches detector response in time

Final Simulation

• MCNP gives the probability of a neutron scatter in pixel $n$ at time $t$ after source event given detection in alpha pixel $a$

• That probability is blurred/delayed based on detector timing response

• Probabilities converted into counts by binomial sampling based on generator output and time
Neural network training

• First convolutional layer incorporates regions of pixels into intermediate representations ("features")

• "ResNet" architecture employed for feature development
  – Each block predicts residuals from previous block through "skip connections," allowing for iterative function approximation

• Dropout used to promote orthogonality at feature layer
  – During training each output value could be temporarily set to zero → forces network to match neurons to features

• Network depth determined by training with single output layer:

<table>
<thead>
<tr>
<th>Depth (s/500epoch)</th>
<th>Training time (s/500epoch)</th>
<th>Time to stability (epochs)</th>
<th>Loss Training</th>
<th>Loss Validation</th>
<th>Parameters</th>
<th>RMSE (test)</th>
</tr>
</thead>
<tbody>
<tr>
<td>101</td>
<td>21032</td>
<td>93</td>
<td>0.0009</td>
<td>0.023</td>
<td>43013633</td>
<td>1.34</td>
</tr>
<tr>
<td>50</td>
<td>3050</td>
<td>&gt;500*</td>
<td>0.0062</td>
<td>0.023</td>
<td>2560000</td>
<td>1.35</td>
</tr>
<tr>
<td>10</td>
<td>2010</td>
<td>152</td>
<td>0.0226</td>
<td>0.051</td>
<td>547633</td>
<td>1.328</td>
</tr>
<tr>
<td>8</td>
<td>2103</td>
<td>100</td>
<td>0.0662</td>
<td>0.1638</td>
<td>1160433</td>
<td>2.108</td>
</tr>
<tr>
<td>6</td>
<td>2108</td>
<td>30</td>
<td>0.3989</td>
<td>0.4118</td>
<td>3724997</td>
<td>4.3767</td>
</tr>
</tbody>
</table>


Results

Maximum errors corresponded to nearly complete obstruction of neutron pixels

<table>
<thead>
<tr>
<th>Measurement time (s)</th>
<th>dX RMSE (cm)</th>
<th>dY RMSE (cm)</th>
<th>dθ RMSE (°)</th>
</tr>
</thead>
<tbody>
<tr>
<td>600</td>
<td>0.4912</td>
<td>0.6479</td>
<td>0.6776</td>
</tr>
<tr>
<td>300</td>
<td>0.4904</td>
<td>0.6485</td>
<td>0.6774</td>
</tr>
<tr>
<td>120</td>
<td>0.4904</td>
<td>0.6485</td>
<td>0.6774</td>
</tr>
<tr>
<td>60</td>
<td>0.4904</td>
<td>0.6485</td>
<td>0.6774</td>
</tr>
<tr>
<td>30</td>
<td>0.4904</td>
<td>0.6485</td>
<td>0.6774</td>
</tr>
</tbody>
</table>

Because they were trained using scaled data, network predictions are robust to measurement time/Poisson noise

RMSE: 0.49cm (X), 0.65cm (Y), 0.68° (θ)
Reconstruction after algorithm

| Actual object |

<table>
<thead>
<tr>
<th>Network Accuracy</th>
<th>Dimension error after reconstruction</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>dx (cm)</strong></td>
<td><strong>dy (cm)</strong></td>
</tr>
<tr>
<td>Actual offsets</td>
<td>12.2</td>
</tr>
<tr>
<td>Network output</td>
<td>11.5</td>
</tr>
<tr>
<td>Error (%)</td>
<td>5.7</td>
</tr>
</tbody>
</table>
Conclusions

- Neural networks are a good tool to recover array position information in NMIS system
- Accuracy is sufficient to allow tomographic image reconstruction
Future work

• Incorporate uncertainty in neural network predictions: network should raise flag if prediction is low confidence.

• Sensitivity study for portable NMIS: is there a better configuration of number/size of detectors that provides better information?
NSSC Experience Highlights

Hiking in Muir Woods following 2017 UPR in Walnut Creek

Data Science Summer Institute 2019
Acknowledgements

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Categorical approximation for uncertainty

Neural networks* as classifiers converge to the Bayesian posterior distribution conditioned on the inputs as priors.

Network feature examination

- Primarily vertical lines of varying width
- Network learning to identify coincident neutron pixels→ how many neutron pixels are in each alpha cone
- Suggests improvement possible by using narrower neutron pixels

| ![Weights for first convolution layer. Vertical white areas next to darker areas indicate that these neurons respond to vertically oriented edges](image) |
Alpha channel timing distributions

A

B

C

D
Pre-trained network weights

![Training Graph](image1)

![Validation Graph](image2)
New array design trade space

1 inch pixels, 78° arc

½ inch pixels, 44° arc
Analysis of residuals

A

B

C

D

E