Enabling A Deep Neural Networks based 3D Data Reconstruction Chain for Wire-Readout LArTPCs


July 10, 2020
**Goal:** Application of ML-based 3D reconstruction* to LArTPC.

Related Presentation

*F. Drielsma, “Scalable, End-to-End Deep Learning Based Data Reconstruction Chain for 3D Particle Imaging Detectors”*
From 2D wire hits to 3D points

Reconstructed 3D points using all valid wire intersections from 2D views

True 3D trajectory image

An example of ghost points from false combinations of wire hits

How do ghost points arise?

Seeking a solution to produce high quality 3D points to enable 3D data reconstruction chain
Deghosting - Clean 3D Image for LArTPC

1. reconstruct 3D points w/ machine learning algorithm, or
2. improve existing 3D point reconstruction algorithms w/ ML techniques (this talk)

Unless specified, examples shown in this talk are from ICARUS detector simulation using Cluster3D* point reconstruction.

Alternative 3D point reconstruction algorithms can be used.

Cluster3D
- developed by Tracy Usher (SLAC)
- aims to reconstruct 3D points in high efficiency,
- with trade off of more ghost points

Related Presentation
T. Wongjirad, “DL In MicroBooNE”
Deghosting w/ Sparse UResNet

In addition to 5-type segmentation, add an extra classifier in Sparse UResNet to predicts binary semantic segmentation (ghost vs. non-ghost).

Related Presentations
L. Domine, “Scalable 3D Semantic Segmentation and Point Proposal Network for large-scale high resolution particle imaging detectors”
R. Itay, “Using Sparse Convolutional Neural Networks in MicroBooNE”

See arxiv:1903.05663 for details on the architecture & sparse convolutions
Deghosting Results

True 3D trajectory image

Network Input
Reconstructed 3D points by Cluster3D

Network Output
After removal of predicted ghost points
Deghosting Performance

92%  
Fraction of ghost voxels correctly predicted

94%  
Fraction of non-ghost voxels correctly predicted

Remaining mistakes are “reasonable”.

Predicted non-ghost points
Deghosting Mistakes

True ghost voxels mistakenly predicted as non-ghost

True non-ghost voxels mistakenly predicted as ghost

Ref: True 3D Image

Peaked at 1 voxel around true trajectory in log scale
Deghosting Performance

Non-smooth local fluctuations in reco. 3D pts

Remaining mistakes are “reasonable”
- expected from the local fluctuations in reco. 3D pts
- misidentified ghost (or non-ghost) points are in the neighborhood of the true trajectory
- overall event topology is preserved

92%
Fraction of ghost voxels correctly predicted

94%
Fraction of non-ghost voxels correctly predicted
Deghosting Performance Breakdown

5-classes semantic segmentation on predicted non-ghost voxels

<table>
<thead>
<tr>
<th>Class</th>
<th>Fraction of true nonghost correctly predicted</th>
</tr>
</thead>
<tbody>
<tr>
<td>EM shower</td>
<td>92.6%</td>
</tr>
<tr>
<td>Track</td>
<td>97.5%</td>
</tr>
<tr>
<td>Michel</td>
<td>95.9%</td>
</tr>
<tr>
<td>Delta</td>
<td>90.5%</td>
</tr>
<tr>
<td>LowE</td>
<td>71%</td>
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Semantic Segmentation After Deghosting

5-classes semantic segmentation on predicted non-ghost voxels

Confusion matrix (rows sum up to 1)
Enabling physics analysis: the example of Michel electrons
Michel electrons analysis

<table>
<thead>
<tr>
<th></th>
<th>Identification</th>
<th>Clustering</th>
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<tbody>
<tr>
<td>Purity</td>
<td>98%</td>
<td>91%</td>
</tr>
<tr>
<td>Efficiency</td>
<td>93%</td>
<td>88%</td>
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BONUS: Applying to other wire LArTPCs (ProtoDUNE-SP)

ProtoDUNE-SP

- a ~740-ton LArTPC prototype for DUNE
- similar to ICARUS detector with different geometry and wiring layouts

Related Presentation (Neutrino 2020 Poster #512)
K.V. Tsang, “Machine Learning Based Reconstruction of Neutral Pion in ProtoDUNE-SP”

Example of a neutral pion decay
Summary

- Combination of the `cluster3d` algorithm and deep neural network-based “deghosting” method enables our 3D reconstruction chain for wire LArTPCs
  - Can be adopted to different experiments (SBN, ProtoDUNE-SP), and possibly DUNE-FD
  - Also applicable to different 3D point reconstruction algorithms (SpacePointSolver, WireCell ...)

- Preliminary results show that the reconstruction chain performance is retained.

- Next steps: finish integrating with the rest of the reconstruction chain:
  - EM shower clustering,
  - Interaction clustering,
  - Particle flow reconstruction,
  - Etc

*D. Koh, “Proposal-free Deep Sparse Convolutional Neural Network for 3D Pixel Clustering”*
Backup: Michel Electron Reco. w/ Open Dataset

3D Semantic Segmentation

Example of application: finding Michel electron clusters

Straightforward algorithm based on UResNet semantic segmentation output:

1. Select MIP + Michel pixels
2. DBSCAN clustering algorithm
3. Simple cuts (Michel attached to the edge of a muon)

<table>
<thead>
<tr>
<th>Identification</th>
<th>Purity</th>
<th>Efficiency</th>
</tr>
</thead>
<tbody>
<tr>
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<td>97.3%</td>
<td>93.4%</td>
</tr>
<tr>
<td>Clustering</td>
<td>96%</td>
<td>96%</td>
</tr>
</tbody>
</table>

including analysis cut of minimal 10px for Michel electron cluster size

L. Domine, "Scalable 3D Semantic Segmentation and Point Proposal Network for large-scale high resolution particle imaging detectors"