Interaction Clustering in Liquid Argon Time Projection Chamber using Graph Neural Net

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Liquid Argon Time Projection Chamber

Time Projection Chamber (TPC) is one type of modern detector techniques, which features high resolution in 3D position reconstruction. Because of this, Liquid Argon (LAr) TPCs are widely used in neutrino experiments, such as MicroBooNE [1], ICARUS [2] and DUNE [3]. Typical single-phase LArTPC usually consists of cathode plane, field cage and anode wire planes. The electrons generated in energy deposition are drifted towards anode planes. There are three fine-pitched wire planes, named induction, second induction, and collection planes, for collecting and reading out the ionization electrons, and for reconstructing the projected transverse position.

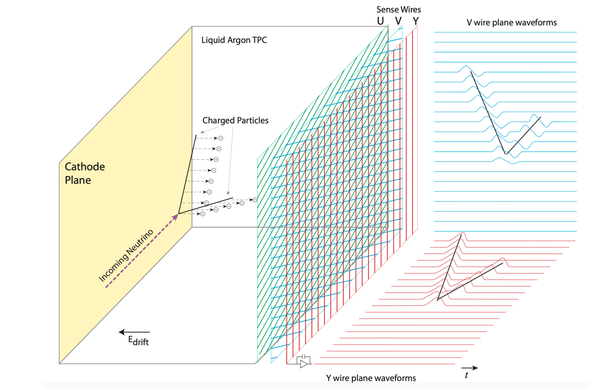
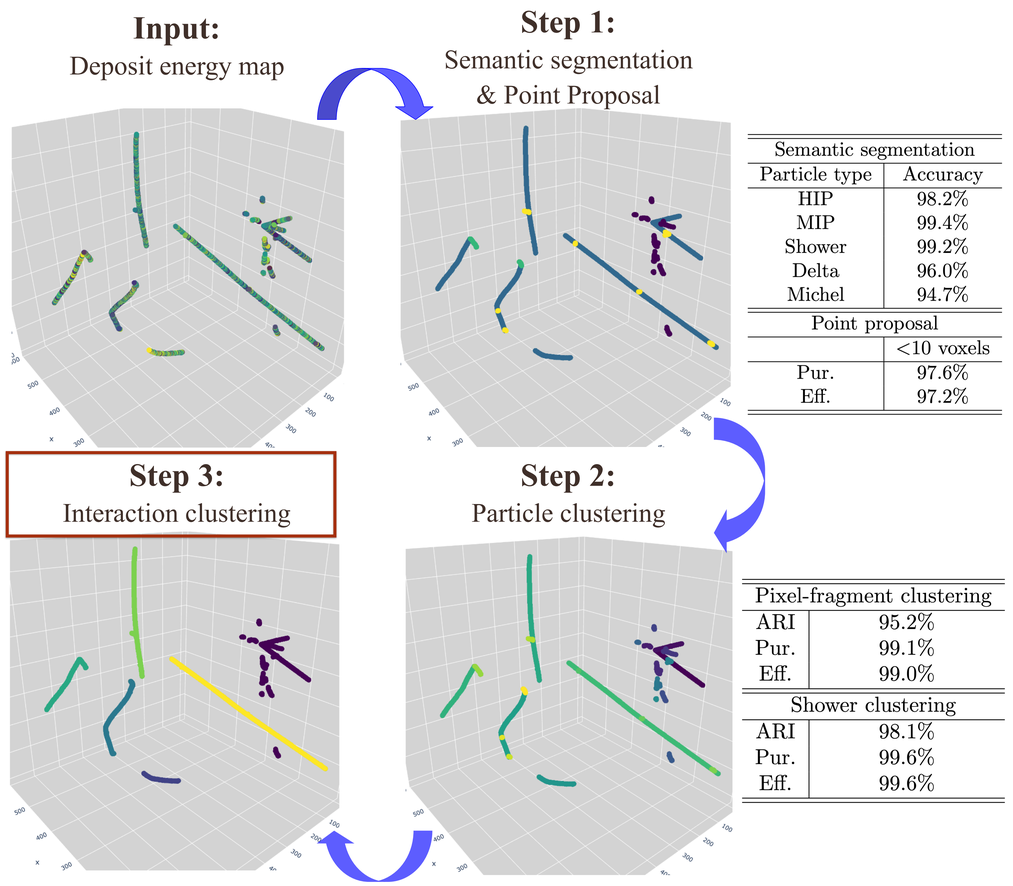


Fig. 1: Typical schematic of LArTPC, taken from MicroBooNE [1].

Reconstruction Chain

The research team at SLAC is leading the development of Machine Learning (ML) based full data reconstruction chain for LArTPCs. The chain aims at providing full reconstructed event information with high precision and efficiency, allowing for inference in neutrino oscillation physics. The input of the chain is pixel-wise 3D map of deposit energy. There are mainly three sequential modules in the reconstruction chain:

1. **Semantic segmentation & Point proposal (See also post #373)**
   UResNet [4] architecture is used to conduct pixel-wise image classification (5 classes: HIP, MIP, EM shower, delta, Michel e^-). It also extracts important informations, such as start/end points.
2. **Particle clustering (See also post #321 & #317)**
   The segments of same semantic types are clustered into particle groups, including pixel-to-fragment (dense) clustering and shower clustering.
3. **Interaction clustering**
   Clustered particle groups are clustered into interaction groups, distinguishing neutrino interaction induced topologies from comic ray induced single track and shower.



Semantic segmentation	
Particle type	Accuracy
HIP	98.2%
MIP	99.4%
Shower	99.2%
Delta	96.0%
Michel	94.7%
Point proposal	
	<10 voxels
Pur.	97.6%
Eff.	97.2%

Pixel-fragment clustering	
ARI	95.2%
Pur.	99.1%
Eff.	99.0%
Shower clustering	
ARI	98.1%
Pur.	99.6%
Eff.	99.6%

Fig. 2: Schematic of Reconstruction chain & their performance.

Interaction Clustering using Graph Neural Network

Graph Neural Network (GNN) is used in both particle and interaction clustering. During interaction clustering, each particle group is represented by "node" and relation between each pair of particle groups is represented by "edge" in a complete graph. Numbers of node and edges features are fed into GNN, which outputs the score of edges that can be used for identifying the particles that belong to the same interaction.

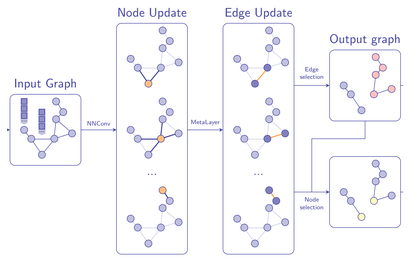


Fig. 3: Schematic of GNN.

Node features:
- Centroid
- Covariance matrix + PCA
- Start/end point + direction
- Energy mean & standard deviation
- Semantic type

Edge features:
- Displacement vector (+ variations)
- Closest points of approach

Performance

The training and testing samples are 3D images with 768 pixels on each dimension and 3mm for each pixel. There are two types of interactions in the samples: neutrino-like and cosmic-like. Neutrino-like interactions are simulated by generating particles from the same vertex with random direction. Cosmic-like interactions are single muon tracks or single cosmic induced showers. Adjusted rand index (ARI) is used for quantifying the goodness of clustering.

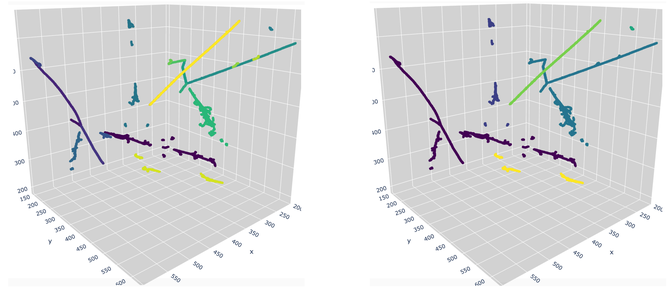


Fig. 4: A sample of interaction clustering. (Left) 3D image of particle groups before clustering. (Right) Clustered interactions.

N_v	ARI	PUR	EFF
1	98.6%	99.6%	99.7%
2	98.7%	99.6%	99.4%
4	98.0%	99.6%	98.9%

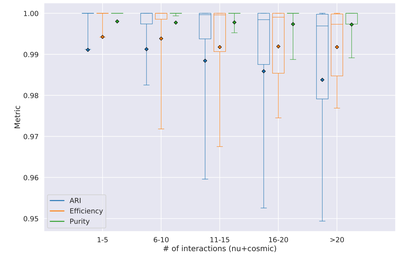


Fig. 5: ARI, purity and efficiency of interaction clustering as a function of number of interactions.

Reference:

[1] "Design and construction of the MicroBooNE detector", MicroBooNE Collaboration, JINST 12 P02017 (2017)

[2] "Design, construction and tests of the ICARUS T600 detector", ICARUS Collaboration, Nuclear Instruments and Methods in Physics Research Section A 527, 329-410 (2004)

[3] "Long-baseline neutrino facility (LBNF) and deep underground neutrino experiment (DUNE) conceptual design report, volume 4 the DUNE detectors at LBNF", DUNE Collaboration, arXiv: 1601.02984 (2016)

[4] "Scalable deep convolutional neural networks for sparse, locally dense liquid argon time projection chamber data", L. Dominé and K. Terao, arXiv: 1903. 05663 (2019)

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