Deep Learning Based Event 4-Dimensional Track Reconstruction in LArTPC Detector

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1. Introduction

The liquid argon time projection chamber (LArTPC) is a popular detector technology widely used in recent and upcoming accelerator neutrino experiments. LArTPC features a low energy threshold and high spatial resolution that allow for comprehensive reconstruction of event topology. A set of LArTPC detectors are used and will be used within the ICARUS, MicroBooNE, SBN, and DUNE collaborations ([1, 2, 3, 4]) to precisely measure neutrino-argon interaction cross sections, detect anomalies such as dark matter or sterile neutrion, search for CP-violation in lepton sector, and determine the neutrino mass hierarchy.

Understanding the structures of an event is vital for interaction identification and understanding the physics processes that occurred in the detector. Reconstruction of events, especially the track structure, is one of the most challenging tasks in analyzing the data from current and future massive LArTPC detectors.

Event 4-dimensional (4D) track reconstruction is the task to create a 4D representation (3D vertex together with 1D energy deposit) of the particle track inside LArTPC detectors with data taken from multiple 2D readout channels. In this work, we introduce a novel 4D imaging method, which reconstructs tracks with energy deposit and sparsity information through a simple transformer-based neural network. The resulting 4D track of an event provides an excellent starting point for further analysis tasks and realizes the true power of the tracking calorimetry in LArTPC detectors.

2. Substantial section

2.1 LArTPC and Challenge of Event Reconstruction

A LArTPC detector, with wire plane based design, has cathode and anode planes separated by a long drift distance to create an electric field in the large volume of liquid argon. Passing through the media, an ionizing particle ionizes and excites argon atoms, producing charges (electrons and ions) along its track. The ionization electrons drift along the electric field toward the anode wire planes, inducing currents in the wires which are read out as a series of digitized waveforms, which can be viewed as a sequence of 2D (time vs. wire) projection images of particle trajectories. Figure 1 demonstrates the working principle of a LArTPC detector and the operating principle can be found in [5].

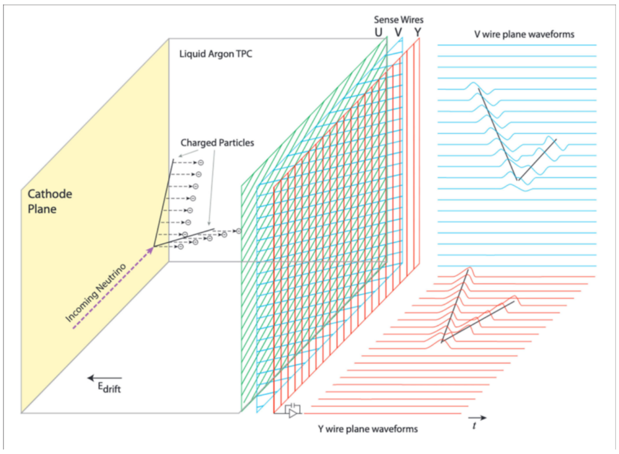

Fig. 1: Working principle of LArTPC detector.

In LArTPC detectors, multiple anode wire planes, each with parallel wires oriented at different angles, allow 3D vertex reconstruction of the ionization energy deposition while the deposited energy at each point along the track can be reconstructed from the amplitude of the recorded digitized waveforms. For such an imaging detector, one critical step is signal processing that reconstructs the original charge projections from the recorded 2D images.

However, the wire plane readout gives rise to reconstruction difficulties and ambiguities due to the projective geometry. For tracks that have small angles to the plane perpendicular to the electric field, the ionization electrons from the entire track produce simultaneous pulses in all wires in their drift path, resulting in the ambiguities growing exponentially with the multiplicity of simultaneously hit wires. In addition, these conditions are often occurring for large electromagnetic showers, and near particle interaction vertices where track multiplicity is high. Those challenges are difficult to be solved by traditional algorithms [6, 7], and are summarized in report [8].

2.2 Deep Learning Based Reconstruction Method

In this manuscript, we describe a new 4D imaging method which takes advantage of key features of the LArTPC detector to directly reconstruct the ionization density in 3D voxel. In order to resolve many of the ambiguities caused by the lack of pixel-level information, we develop a deep-learning-based algorithm to learn the relationship between the measured ionization charge information, its sparsity, its arrival time, and the detector wire geometry, so that it is able to reconstruct the 4D imagine of an energy deposition, hence the event 4D track.

Transformer models ([9]) are efficient in processing sequential data, while the attention mechanism helps to capture the dependencies among the input points. This feature makes them well-suited for reconstructing the 4D tracks of ionizing particles in a LArTPC detector. We develop a transformer model to reconstruct the 4D vertex of events using the time and charge information that read out from the wire planes. To train the model, we generate a small amount of samples via Monte-Carlo simulation and engineer the input single channel 2D image into 3 channels, one processed with filtered deconvolution, two with geometry information baked in. With the test samples, we demonstrate the trainability of the transformer model.

One disadvantage of transformer models is that it requires vast amounts of training data to achieve effective generalization ([10]). Meanwhile, transformers struggle with modeling long input sequences, despite their advancements in natural language understanding and generation. To solve these problems, we proposed a solution that enables the model to be trainable with relatively small training samples and to work around the limitation of processing long input sequences. The initial tests show that this method can solve the crucial limitations of conventional methods and improve event reconstruction accuracy.

3. Conclusion and Discussion

In this work, we introduce a deep neural network to pre-process events taken from LArTPC detectors and improve the event 4D track reconstruction. We propose a transformer based model to demonstrate the application of deep learning technology in physics research. We propose a method to make it possible that transformer model can be trained with a small dataset in scientific research.

By combining domain knowledge (e.g., LArTPC wire chamber working principle) and deep learning philosophy (attention mechanism), this method shows significant improvements over traditional methods. The clean and accurate event 4D track provides an excellent starting point for subsequent interaction identification or pattern recognition procedures.

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