Reconstruction of atmospheric neutrinos and muons using Machine Learning-based methods in JUNO

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Abstract. The Jiangmen Underground Neutrino Observatory (JUNO), located in Southern China, is a multi-purpose neutrino experiment that consists of a 20-kton liquid scintillator detector. The primary goal of the experiment is to determine the neutrino mass ordering (NMO) and measure other neutrino oscillation parameters to sub-percent precision. Atmospheric neutrinos are sensitive to NMO via matter effects and can improve JUNO's overall sensitivity in a joint analysis with reactor neutrinos; Atmospheric muons contribute to one of the most important background sources to neutrino signals. Good capability of reconstructing atmospheric neutrinos and muons in JUNO is crucial for its physics goal.

In this contribution, we present a novel multi-purpose reconstruction method for atmospheric neutrinos, muons and other physics events at similar energies (few GeV to tens of GeV) by combining PMT waveform analysis and machine learning techniques. Multiple machine learning approaches, including planer, spherical, and 3-dimensional models, as well as other novel techniques in improving reconstruction precision, are discussed and compared. We show the performance of reconstructing atmospheric neutrino's directionality and energy using Monte-Carlo simulations, and demonstrate that this method can achieve unprecedented reconstruction precision for multiple physics quantities and fulfils the needs of JUNO. This method also has the potential to be applied to other liquid scintillator detectors.

1 Introduction

JUNO is a multi-purpose neutrino experiment located in the Guangdong province of China. The JUNO central detector (CD) consists of 20-kton liquid scintillator (LS). The main physics goal is to determine the neutrino mass ordering (NMO) by measuring reactor neutrinos from nearby nuclear power plants. The sensitivity of NMO can be enhanced by measuring atmospheric neutrino oscillations. Information of neutrinos' energy and directionality is essential to oscillation analyses since the oscillation probabilities are dependent on energy and distance travelled. However, reconstructing atmospheric neutrino events in LS are challenging, since traditional LS detectors do not offer direct track information. Moreover, the Cherenkov light is about two orders of magnitude weaker than scintillation light, making it very difficult to be utilised for reconstruction.

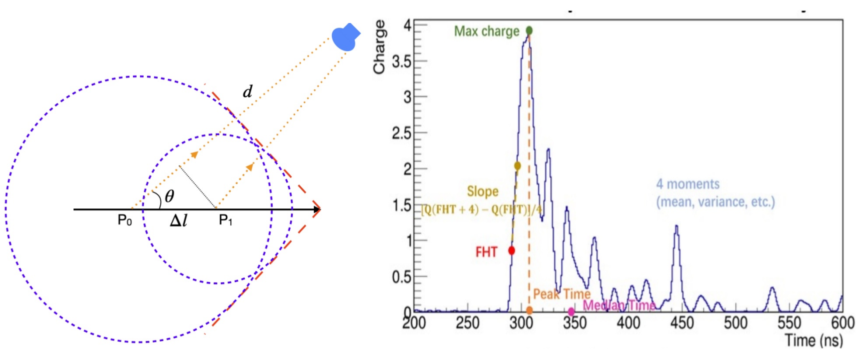

Figure 1: (Left) Illustration of the scintillation light (orange dashed lines) from a charged particle track (black solid line) reaching a PMT. (Right) An example of a PMT waveform together with a set of defined features.

2 Methodology

The light seen by PMTs in the JUNO CD is a superposition of light from many points on the particle tracks in the detector. Fig. 1 (left) shows an illustration of scintillation light from a charged particle track seen by one PMT. The number of photo-electrons (PEs) seen by a PMT as a function of time is determined by event topology, which are reflected in the PMT waveforms. Therefore, PMT waveforms would contain all the physical quantities relevant for physics analyses such as energy, direction, and particle type. In principle, PMT waveforms can be used as input to reconstruction algorithms directly. However, this is very computationally expensive given the large amount of PMTs present in the CD. Therefore, in order to simplify the task, we first extract features from the waveforms that can be used as input to ML models. These include:

- Total charge (nPE), which is calculated by integrating the charge over the entire readout time window;
- First hit time (FHT), which is calculated by using a constant fraction discriminator method with a threshold of 20%
- Slope, which describes the average slope of the deconvoluted waveform in the first 4 ns after the first hit time
- Charge ratio, which is defined as the ratio of charge in the first 4 ns after FHT to the total charge

Fig. 1 (right) shows an example of a waveform from one of the PMTs and the extracted features. Feature importance studies are performed to select final set of features that are used for the ML models.

3 Machine Learning Models

Convolutional Neural Network (CNN) [1] is a deep learning algorithm that is very powerful for analysing visual data, and has been used widely in particle physics experiments. Features extracted from PMTs in JUNO CD form image-like data, which is well-suited for CNN models.

Different approaches have been developed and performances are compared. The first approach involves projecting the spherical data onto a planar surface, allowing the use of various state-of-the-art machine learning models, such as EfficientNetV2 [2]. The second approach utilizes a model based on DeepShere [3], a graph convolutional neural network (GCNN) specifically designed to process spherical data. Lastly, a 3D model based on PointNet++ [4] is employed, which processes the PMT data as a 3D point cloud. The details of these three approaches are discussed in the following subsections.

3.1 Planar Model: EfficientNetV2

In JUNO CD, every single PMT can be considered as a pixel, and for each waveform feature the combination of all PMTs forms a spherical image-like signal. Inspired by ImageNet classification competition, the spherical signal is projected onto a planar representation, and then the direction of the incident neutrino is reconstructed with the state-of-the-art CNN model, EfficientNetV2 [2]. It is known for its superior performance and shorter training time compared to traditional CNNs. For this study, we used the EfficientNetV2-S version in PyTorch implementation.

To integrate this planar model, the PMTs are projected onto a two-dimensional $\theta - \phi$ grid. The grid size of 128×224 is chosen to ensure each grid cell corresponds to at most one PMT. All the extracted PMT features are filled into the $\theta - \phi$ grids, which are then stacked together and fed into the model. Fig. 2 shows an illustration of the EfficientNetV2-S model architecture.

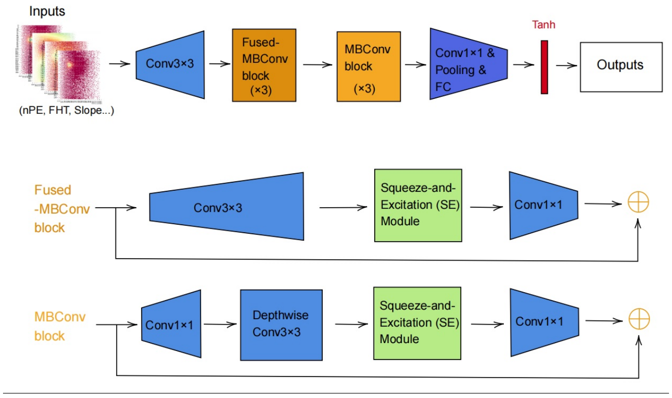

Figure 2: Illustration of the EfficientNetV2-S model architecture. [2]

3.2 Spherical CNN: DeepSphere

DeepShere is a graph convolutional neural network (GCNN) model originally developed for cosmology studies to deal with data distributed on a sphere [28]. One of the major advantages DeepShere provides is that it avoids projecting the data onto a planar surface and maintains rotation covariance, meaning that a rotation of the input variables causes the same rotation of the predicted value.

The main idea behind DeepShere is to model the spherical data as a graph of connected pixels, and perform graph convolution based on spectral graph theory. To adapt to DeepShere, the spherical surface formed by the PMTs is pixelised using the HEALPix scheme [5], which divides the surface into $12 \times N^2$ equal-sized pixels. In this study, $N_{side} = 32$ is used, resulting in a total of 12,288 pixels, which is less than the total number of PMTs. Since for some pixels they cover more than one PMT, the total charge is calculated as the sum of all PMTs within that pixel, while the first hit time (FHT) is taken to be the earliest. The other features are calculated by simply averaging the values of the PMTs. Each pixel is then represented as a graph vertex before being fed into the model. Fig. 3 shows the architecture of the model developed based on DeepSphere.

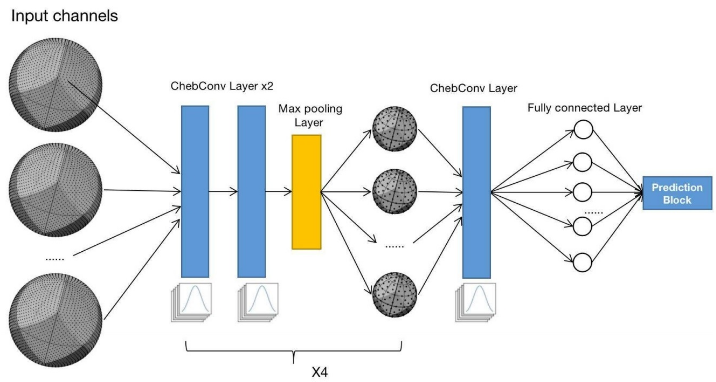

Figure 3: Illustration of the DeepSphere model architecture.

3.3 3D point-cloud: PointNet++

Each PMT within the JUNO CD can be regarded as an individual discrete point. After the PMT waveform feature extraction, each event can be represented by a 3D point-cloud data, where each point contains the information of the three coordinates and the extracted features of one PMT. This allows the data to be directly fed into 3D point cloud-based machine learning models.

As shown in Fig. 4, the PointNet++ architecture is designed to recursively sub-sample a small neighborhood from the whole point cloud, group the neighborhood into larger units, and then extract local features with a mini-PointNet. This approach allows PointNet++ to capture fine-grained local features in addition to learning global ones.

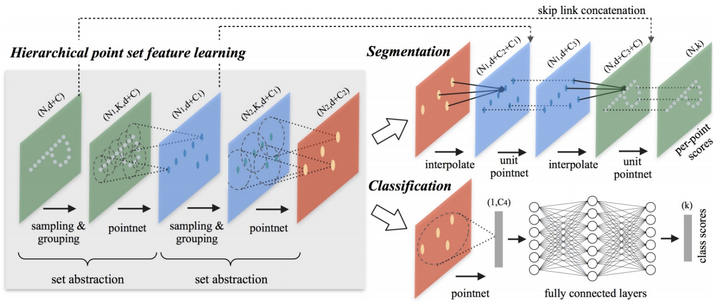

Figure 4: Illustration of the PointNet++ model architecture.

4 Performances

The data sample used to evaluate the performances consists of 135,000 $\nu_\mu\ /\overline{\nu}_\mu$ and 57,000 $\nu_e\ /\overline{\nu}_e$ CC events, of those 80% of the sample are used for training and the rest for testing. The performances are evaluated using the testing sample only.

4.1 Directional reconstruction

The performances of directional reconstruction are evaluated with two parameters: the opening angle α between the true and reconstructed neutrino directions, and the difference between the true and reconstructed zenith angle of the incoming neutrino (θ_ν). Fig. 5 shows the θ_ν resolutions as a function of E_ν for $\nu_\mu\ /\overline{\nu}_\mu$ -CC (left) and $\nu_e\ /\overline{\nu}_e$ -CC (right) events for the three models considered. The resolution improves as E_ν increase. The $\nu_\mu\ /\overline{\nu}_\mu$ -CC events in general have better resolution because of the track-like topology they exhibit inside the detector. For details about our method and results, please refer to our paper published on PRD [6].

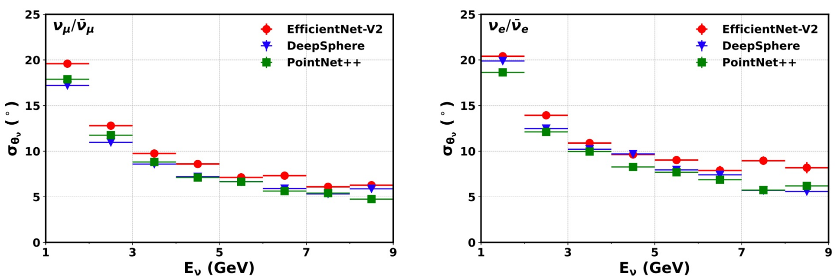

Figure 5: θ_ν resolutions are shown as a function of E_ν for $\nu_\mu\ /\overline{\nu}_\mu$ -CC (left) and $\nu_e\ /\overline{\nu}_e$ -CC (right) events for the three models considered.

4.2 Energy and vertex reconstruction

We can simply modify the final output of the ML models to get other reconstructed quantities such as neutrino energy and interaction vertices. Fig. 6 shows the resolutions for E_{vis} (left) and E_ν (right).

This demonstrates that this method are capable of reconstructing E_ν directly. Unlike Water Cherenkov detectors which rely on reconstructing leptons to infer E_{vis}/direction, for LS detectors, the scintillation light from both leptons and hadrons are visible and therefore can be used to directly reconstructing true neutrinos' properties. We can also achieve good vertex resolution using this method, with ∼20 cm for ν_μ /$\overline{\nu}_\mu$ -CC events and ∼30 cm for ν_e /$\overline{\nu}_e$ -CC events.

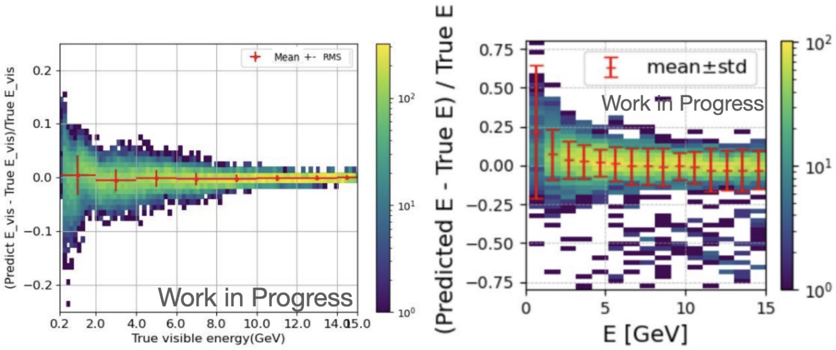

Figure 6: Resolutions for E_{vis} (left) and E_ν (right) based on the spherical and planar models.

5 Reconstruction of cosmic muons

Cosmic muons can propagate through the JUNO CD and interact, producing isotopes which are the dominant background of the Inverse Beta Decay (IBD) signal in JUNO. Therefore, accurately identifying such events is key to JUNO physics analyses. We attempted to utilise the ML method describe above in reconstructing muon events. In particular we focus on reconstructing through-going muons and muon showers using the DeepSphere model.

5.1 Muon tracks

In the attempt of reconstructing muon tracks, a data sample of ∼93 through-going muons are produced and four features are extracted (FHT, nPE, nPE ratio, Slope) as inputs to the DeepSphere model. An illustration of such events is shown on fig. 7 (left). The variables of interest are the incident/exiting point of the track (A1 and A2 respectively), and also the angle between the true and reconstructed track α, which is the quantity used to evaluate the directional reconstruction performance. The resolution of α is defined as the 68% quantile from the α distribution. The resolution of α as a function of the distance from detector center (r) is shown on fig. 7 (right). The resolution is slightly worse at small r due to the lack of events as r approaches zero. The resolution are significantly worse as we move away from the detector center since the track lengths become increasingly short as r increase, making such events harder to reconstruct.

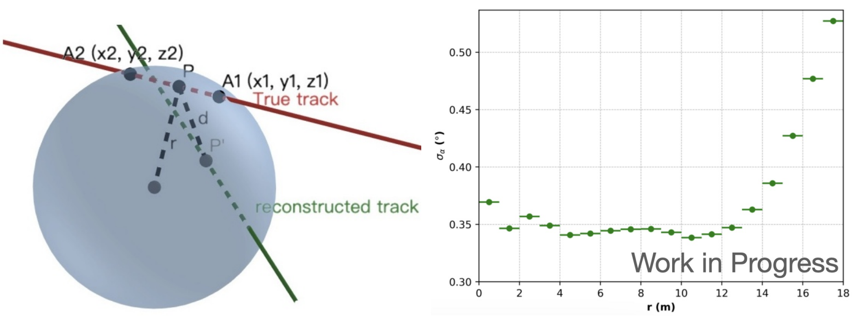

Figure 7: (Left) Illustration of a through-going muon event. (Right) The resolution of α as a function of the distance from detector center (r).

5.2 *Muon showers*

As muons propagate through the CD, they can produce isotopes such as ^{8}He and ^{9}Li along the track which can decay and mimic the IBD signal. In order to reconstruct these events, as well as reconstructing the start/end and centre of showers, we also need to reconstruct the energy deposition (E_{dep}) of muon showers as well as dE/dx of muon tracks to fully reconstruct the whole event. We focus on the E_{dep} of showers since we can reconstruct the muon's track well and we already know the MIP of a muon in LS, which is around 2 MeV/cm. Fig. 8 shows the reconstruction performance of muon showers. The results indicate that this reconstruction method has a great potential on reconstructing such events, with the predicted range close to the true range of the shower contribution. The bias seen from the difference between true and reconstructed E_{dep} is possibly due to interference from the actual dE/dx of muon tracks.

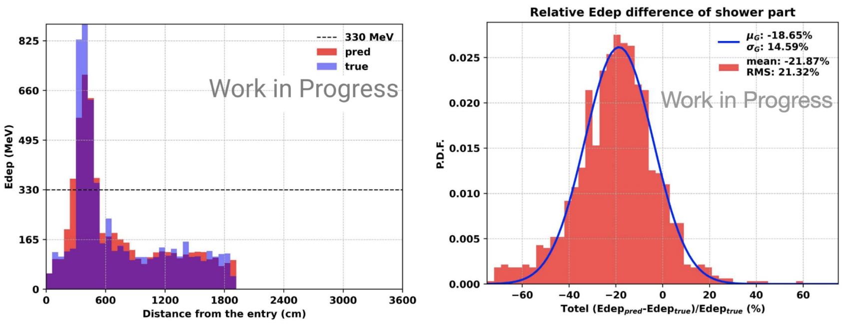

Figure 8: (Left) Comparison between true and reconstructed E_{dep} of a muon shower event. (Right) Difference between true and reconstructed E_{dep}.

6 Summary

This study presents a novel multi-purpose reconstruction method for atmospheric neutrinos, muons, and other physics events at similar energies using PMT waveform analysis combined with machine learning techniques. The proposed method enhances JUNO's ability to determine neutrino mass ordering (NMO) and measure other neutrino oscillation parameters by accurately reconstructing event energy and directionality. Three machine learning models—planar (EfficientNetV2), spherical (DeepSphere), and 3D (PointNet++)—are compared for their performance in reconstructing these events. With multiple performance evaluations using Monte Carlo simulations, the study achieves high precision in gauging various parameters like neutrino directionality, energy, and cosmic muons. The results demonstrate the ML method's capability to achieve unprecedented reconstruction precision and suggest that these techniques could be applied to other liquid scintillator detectors.

References

[1] Y. LeCun et al. "Backpropagation Applied to Handwritten Zip Code Recognition". In: *Neural Computation* 1.4 (Dec. 1989), pp. 541–551.

[2] Mingxing Tan and Quoc Le. "EfficientNetV2: Smaller Models and Faster Training". In: *Proceedings of the 38th International Conference on Machine Learning*. Ed. by Marina Meila and Tong Zhang. Vol. 139. Proceedings of Machine Learning Research. PMLR, 18–24 Jul 2021, pp. 10096–10106.

[3] N. Perraudin et al. "DeepSphere: Efficient spherical convolutional neural network with HEALPix sampling for cosmological applications". In: *Astronomy and Computing* 27 (2019), pp. 130–146.

[4] Charles R. Qi et al. *PointNet++: Deep Hierarchical Feature Learning on Point Sets in a Metric Space*. 2017.

[5] K. M. Górski et al. "HEALPix: A Framework for High-Resolution Discretization and Fast Analysis of Data Distributed on the Sphere". In: *The Astrophysical Journal* 622.2 (Apr. 2005), p. 759.

[6] Zekun Yang et al. "First attempt of directionality reconstruction for atmospheric neutrinos in a large homogeneous liquid scintillator detector". In: *Phys. Rev. D* 109.5 (2024), p. 052005.