PROCEEDINGS OF SCIENCE

Vertex Reconstruction in JUNO

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On behalf of the JUNO collaboration

The Jiangmen Underground Neutrino Observatory (JUNO), currently under construction in the south of China, will be the largest Liquid Scintillator (LS) detector in the world. JUNO is a multipurpose neutrino experiment designed to determine neutrino mass ordering, precisely measure oscillation parameters, and study solar neutrinos, supernova neutrinos, geo-neutrinos and atmospheric neutrinos [1]. The central detector of JUNO contains 20,000 tons of LS and about18,000 20-inch as well as 25,000 3-inch Photomultiplier Tubes (PMTs). The energy resolution is expected to be $3\%/\sqrt{E(\mathrm{MeV})}$. To meet the requirements of the experiment, two algorithms for the vertex reconstruction have been developed. One is the maximum likelihood method which utilizes the time and charge information of PMTs with good understanding of the complicated optical processes in the LS. The other is the deep learning method with the Convolutional Neural Networks, which is fast and avoids the details of optical processes. In this proceeding, we will present the current status of the two algorithms and their performance will also be discussed based on simulation data.

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1. PMTs Configuration

The main factors affecting the resolution of vertex reconstruction include the PMTs transit time spread (TTS) and dark noise (DN). In this study, only 20-inch PMTs from central detector (CD) are used for reconstruction, including 5,000 Hamamatsu dynode PMTs (R12860) and about 13,000 Micro Channel Plates (MCP) PMTs from North Night Vision Technology (NNVT). The TTS of Hamamatsu PMTs and NVVT PMTs is designated as 2.7 ns and 18 ns, respectively, while the mean value of DN rate is designated as 15 kHz and 32 kHz, respectively [2].

2. Time Likelihood Vertex Reconstruction

The vertex of energy deposit in the LS is reconstructed using the timing information of the optical photons detected by the PMTs. Residual hit time $t_{res}(\vec{R}_{rec}, t_{rec}) = t_i - tof_i - t_{rec}$ is used to construct the probability density function (PDF). The PDF for a single photoelectron (PE) is derived from a Monte Carlo (MC) simulation, while the PDF for nPE could be calculated by the following equation:

$$f_n(t_{res}) = nf(t_{res})(\int_{t_{res}}^{\infty} f(x)dx)^{n-1} \tag{1}$$

The PDF for different nPE is shown in Fig. 1 (Left), and the method to describe transit time spread and dark noise from PMTs is shown in Fig. 1 (Right). The event vertex is calculated by minimizing likelihood function: $\mathcal{L}(\vec{R}_{rec}, t_{rec}) = -\sum \ln(f_n(t_{res}))$.

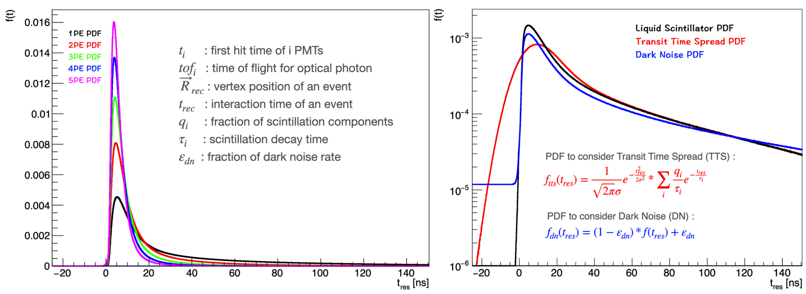

Figure 1: PDF for different nPE (Left). PDF to describe transit time spread and dark noise(Right).

3. Convolutional Neutral Networks Vertex Reconstruction

One of the most popular algorithms for deep learning is supervised learning with Convolutional Neural Networks (CNN). Since CNN needs images as the input, we project PMTs on JUNO CD surface onto a two-dimensional plane and build a 230×126×2 matrix, as shown in Fig. 2. We generate 2 million MC e^+ with energy from 1 to 10 MeV and uniformly distributed within CD as a training dataset. e^+ with discrete energy of 0 MeV, 1 MeV, ..., 10 MeV as a testing dataset, each energy contains 10 thousand events. For each event, we use the hit time of the first arrival photon and number of photoelectrons on each PMTs as input variables, and the energy deposited position (x, y, z) from MC simulation as output variables. After optimization, we use ResNet [3] model with 50 convolutional layers and approximately 35 million parameters. The mean square error is used to define the loss function, where the loss function is minimized by Adam optimizer.

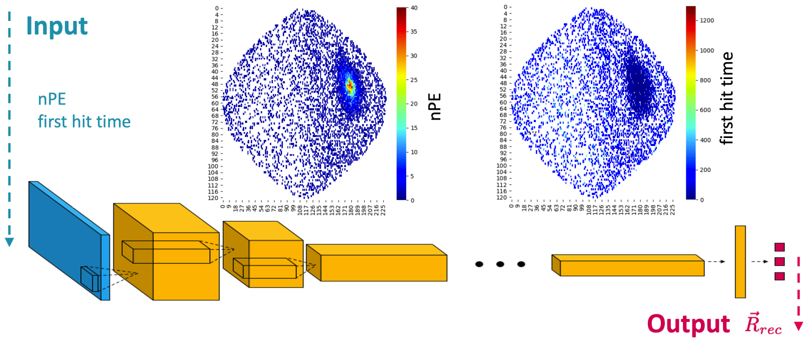

Figure 2: Projection of detector and structure of CNN network.

4. Performance and Conclusion

The vertex resolution as a function of energy for two methods is shown in Fig.3 (Left). The vertex mean bias as function of R^3 is shown in Fig.3 (Right).

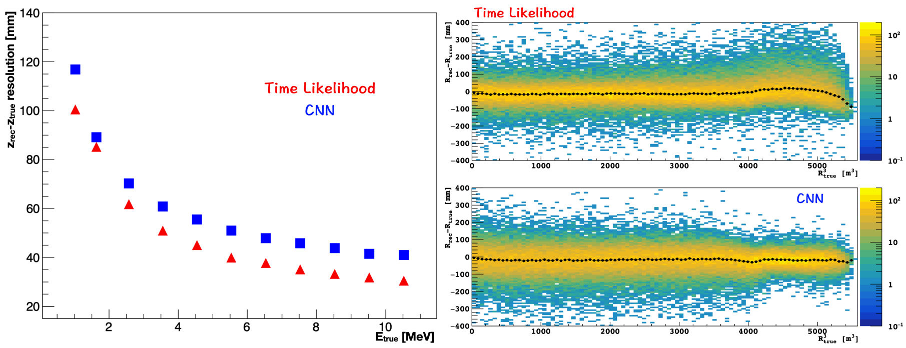

Figure 3: Vertex Resolution vs. Energy (Left). Vertex mean bias vs. R^3 (Right).

To conclude, Time Likelihood outperforms CNN in the central region of detector ($R^3 < 4000$ m^3), while CNN tends to give more accurate prediction in the total reflection region ($R^3 > 4000$ m^3), where the optical processes are more complicated. Moreover, CNN shows no reconstruction bias in the whole detector.

5. Acknowledgments

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References

[1] F. An, et al., J. Phys. G: Nucl. Part. Phys. 43 (2016) 030401

[2] Z.M. Wang, J. Phys. Conf. Ser. 888 (2017) 012052.

[3] K. He, et al., IEEE CONF COMPUT, (2016) pp. 770-778.