Vertex Reconstruction in JUNO

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JUNO Experiment

JUNO Physics: 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, study solar neutrinos, supernova neutrinos, geo-neutrinos, and atmospheric neutrinos. The energy resolution is expected to be $3\%/\sqrt{E(\mathrm{MeV})}$. To meet this requirement, precise vertex reconstruction is essential to correct for detector response non-uniformity. Moreover, vertex information is important in particle identification, background rejection, particle direction reconstruction, etc.

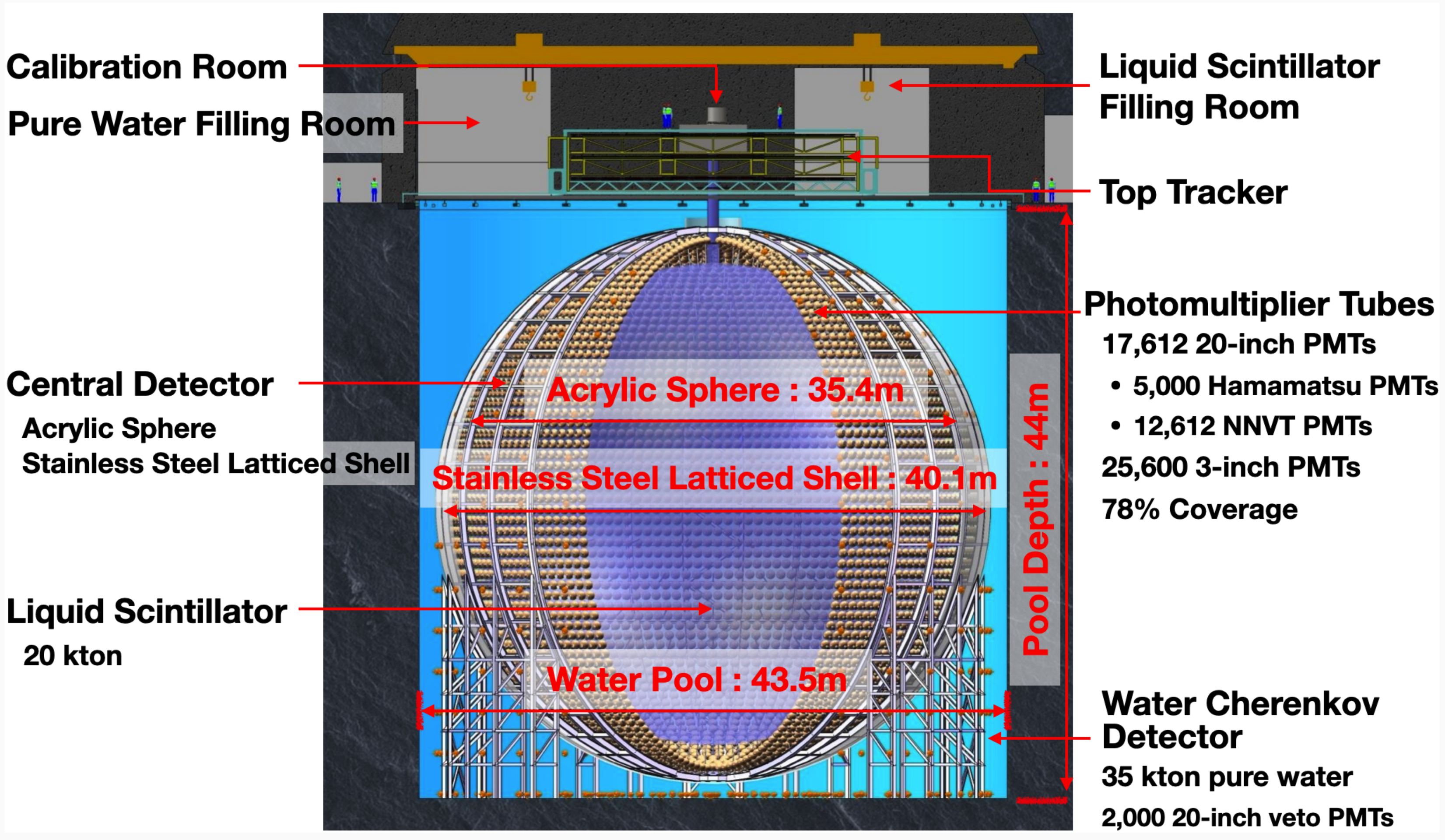

Fig. 1: Schematic view of JUNO detector.

JUNO Detector: The central detector of JUNO contains 20 kton of LS and 17,612 20-inch as well as 25,600 3-inch Photomultiplier Tubes (PMTs). The inner diameter of the acrylic ball is 35.4 m. The main factors affecting the resolution of the vertex reconstruction include the PMT Transit Time Spread (TTS) and Dark Count Rate (DCR). In this study, only 20-inch PMTs from central detector 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 MCP PMTs is designated as 2.7 ns and 18 ns, respectively, while the DCR is designated as 15 kHz and 32 kHz, respectively.

Optical Processes: When neutrinos go through the LS, some of them interact with the LS and the secondary particles emit fluorescent photons. Emitted photons go through a long distance before they are detected by the PMTs. During their propagation in the LS, these photons are likely to be absorbed, reemitted, scattered, or reflected. Additionally, the refractive index is 1.49 for the LS and 1.33 for the pure water. The large difference of refractive indices between two materials results in the large effects of refraction and total reflection at the boundary of two materials, which will affect the time of flight for optical photons. Hence, the optical model is critical for the vertex reconstruction and is important for the JUNO experiment.

Time Likelihood Vertex Reconstruction

The vertex of a scintillation event is reconstructed using the timing information of the optical photons detected by the PMTs.

Residual hit time is used to construct the probability density function (PDF) :

$$t_{i,res}(\vec{R}_{rec}, t_{rec}) = t_i - tof_i - t_{rec} \tag{1}$$

The PDF for a single photoelectron (PE) is derived from a Monte Carlo simulation, PDF for nPE could be calculated by the following equation:

$$f_n(t_{res}) = nf(t_{res})(\int_{t_{res}}^{\infty} f(x)dx)^{n-1} \tag{2}$$

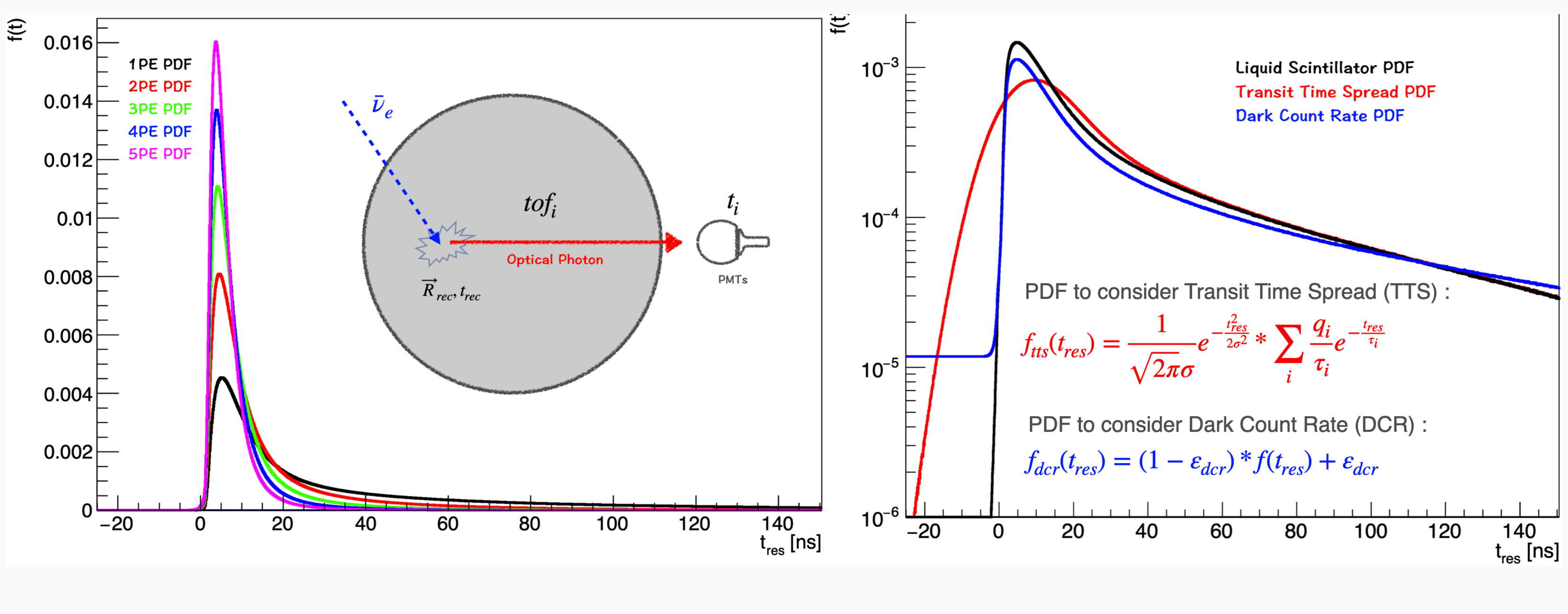

Fig. 2: PDF for different nPE (left). PDF to describe TTS and DCR (right).

In order to reduce the influence of TTS and DCR on vertex reconstruction, the formulas in Fig. 2 (right) is used.

The event vertex is calculated by minimizing the likelihood:

$$\mathcal{L}(\vec{R}_{rec}, t_{rec}) = -\sum_i \ln(f_n(t_{i,res})) \tag{3}$$

where :
t_i : first hit time of i PMTs;
tof_i : time of flight for optical photon;
$\vec{R}_{rec}$: vertex position of an event;
t_{rec} : interaction time of an event;
q_i : fraction of scintillation componentsl;
τ_i : scintillation decay time;
ϵ_{dcr} : fraction of dark count rate.

Deep Learning Vertex Reconstruction

Detector Projection : Sinusoidal-like

- Keep the relative location information of each PMTs;
- Build a 230×126×2 matrix.

Structure and hyper parameters:

- Residual block to go deeper;
- Learning rate: Exponential decay from 10^{-3} to 10^{-6};
- Train steps: 15 epochs with batch size 64;
- Adam Optimizer;
- CNN structure: 50 convolutional layers with about 35 million parameters.

Loss function : $loss = (\vec{R}_{rec} - \vec{R}_{true})^2$

Training:

- Data Set: 5 million Monte Carlo e^+, kinetic energy from 0-10 MeV, uniformly distributed within the central detector;
- Input Variables: (nPE, first hit time) of each PMTs;
- Output Variables: Vertex position $\vec{R}_{rec}$.

Testing:

- Data Set : Monte Carlo e^+, kinetic energy (0, 1, …, 10) MeV, 11 * 10k events, uniformly distributed within the central detector.

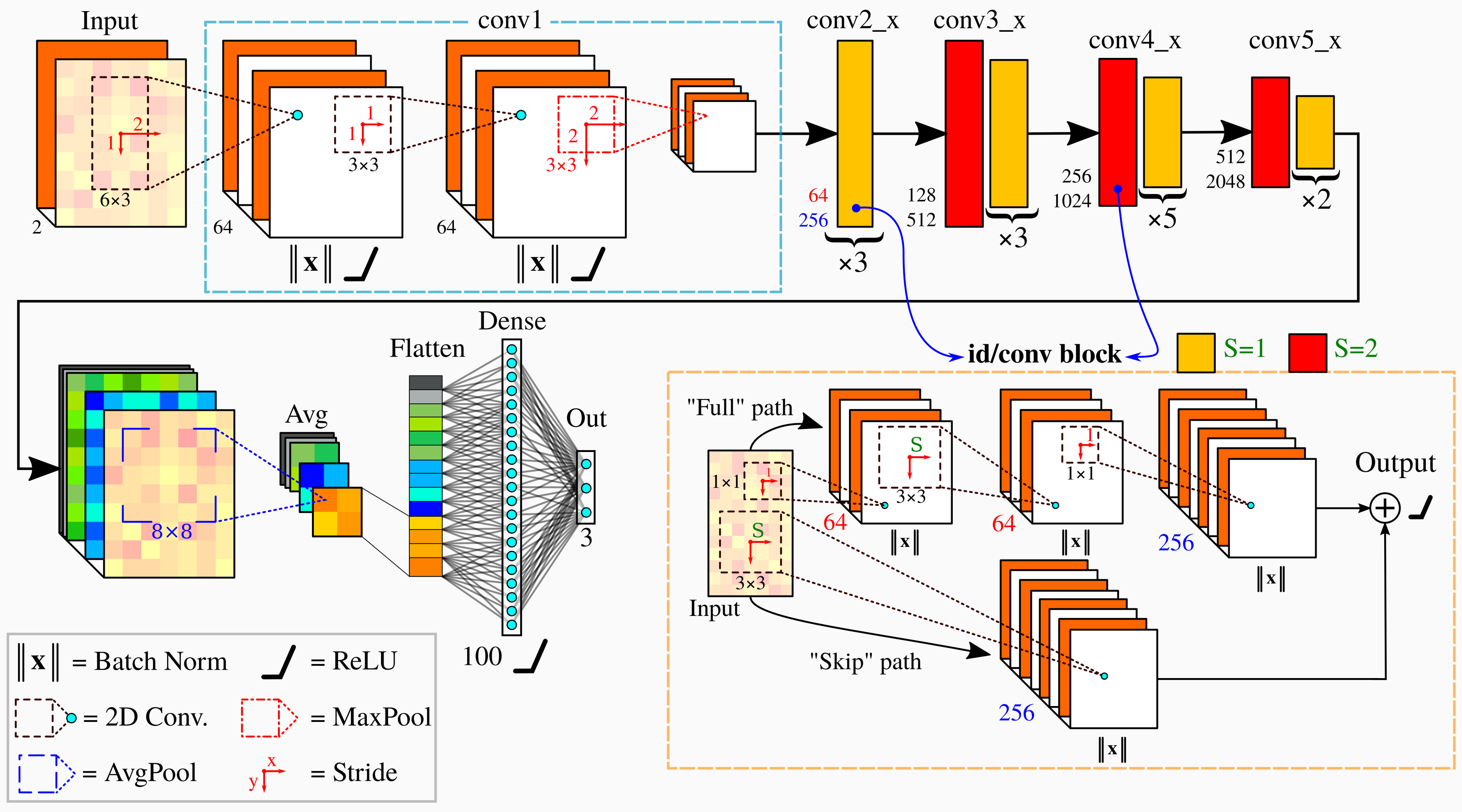

Fig. 3: Structure of the CNN network.

Vertex Reconstruction Performance

By comparing the reconstructed event position and the true position in the Monte Carlo simulation, the reconstructed vertex resolution in each direction could be estimated by a gaussian fit (see Fig.4). The mean values are consistent with zero and the resolutions are similar in the three directions.

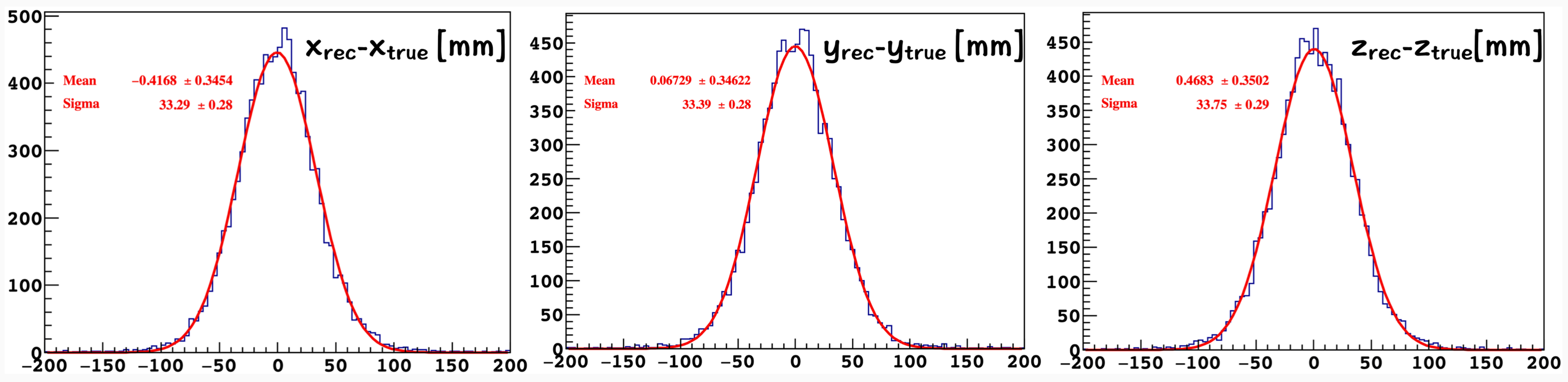

Fig. 4: An example of Gaussian fit in each direction with $E_{\mathrm{kin}} = 7$ MeV, used to extract the bias and the resolution.

The vertex resolution as a function of energy for two methods is shown in Fig.5 (left). In general, Time Likelihood outperforms Deep Learning in the main energy region of reactor neutrinos. Fig.5 (right) shows that Deep Learning tends to give more accurate prediction in the total reflection region (R^3 > 4000 m^3), where the optical processes are more complicated. Moreover, Deep Learning does not introduce reconstruction bias in the whole detector.

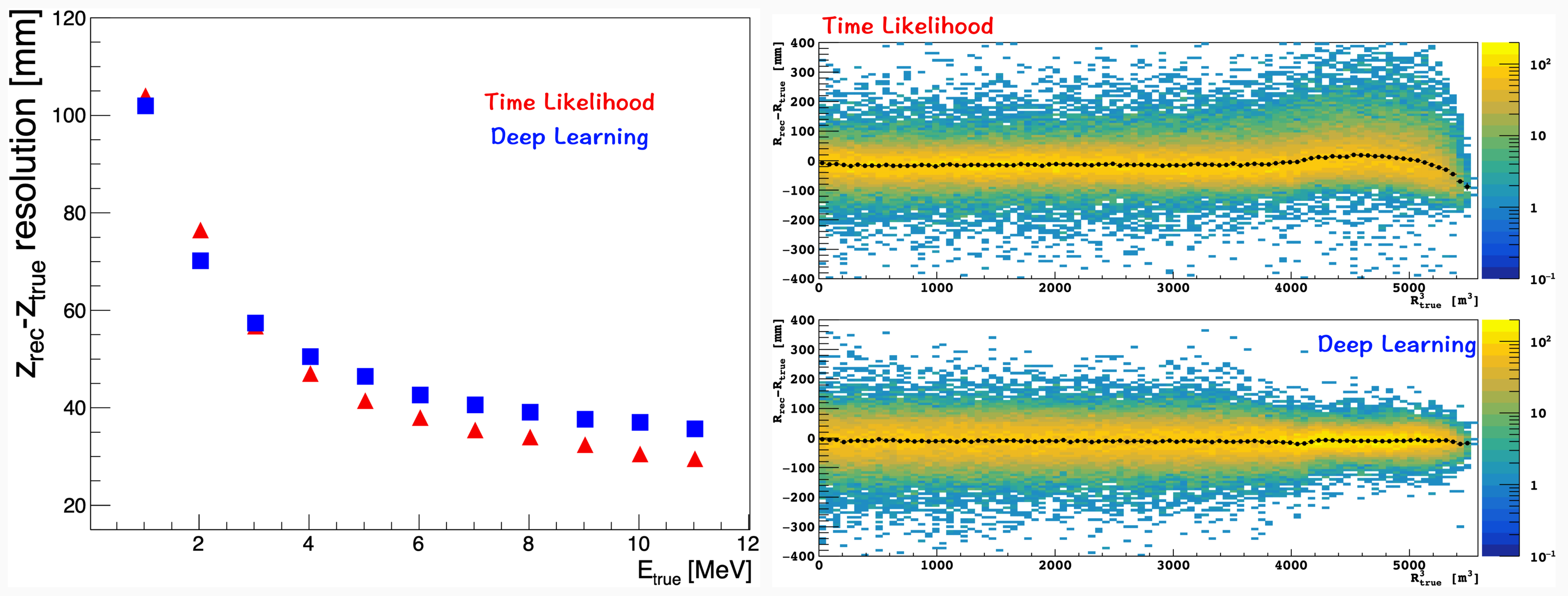

Fig. 5: Vertex Resolution vs. Energy (left). Vertex mean bias vs. R^3 (right).

Besides TTS and DCR, time alignment for each individual PMT and waveform reconstruction will also affects the vertex resolution, which is beyond the scope of this poster.

Conclusion

Two algorithms to reconstruct vertex position for point-like events have been developed. Time Likelihood outperforms Deep Learning in the main energy region of reactor neutrinos, while Deep Learning tends to give more accurate prediction in the total reflection region. Moreover, Deep Learning shows no reconstruction bias in the whole detector. Further studies to remove the bias in the total reflection region for the Time Likelihood, and to take into account the time alignment for each individual PMT and waveform reconstruction effects, and the optimization of the Deep Learning network are ongoing.