Sub-GeV events energy reconstruction with 3-inch PMTs in JUNO

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Abstract

A 20-kiloton liquid scintillator detector is designed in the Jiangmen Underground Neutrino Observatory (JUNO) for multiple physics purposes, including the determination of the neutrino mass ordering through reactor neutrinos, as well as measuring supernova neutrinos, solar neutrinos, and atmosphere neutrinos to explore different physics topics. Efficient reconstruction algorithms are needed to achieve these physics goals in a wide energy range from MeV to GeV. In this paper, we present a novel method for reconstructing the energy of events using hit information from 3-inch photomultiplier tubes (PMTs) and the OCCUPANCY method. Our algorithm exhibits good performance in accurate energy reconstruction, validated with electron Monte Carlo samples spanning kinetic energies from 10~MeV to 1~GeV.

Full Text

Preamble

Sub-GeV Event Energy Reconstruction with 3-inch PMTs in JUNO

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The Jiangmen Underground Neutrino Observatory (JUNO) is designed around a 20-kiloton liquid scintillator detector for multiple physics objectives, including determination of the neutrino mass ordering through reactor neutrinos, as well as measurements of supernova neutrinos, solar neutrinos, and atmospheric neutrinos to explore various physics topics. Efficient reconstruction algorithms are

required to achieve these goals across a wide energy range from MeV to GeV. In this paper, we present a novel method for reconstructing event energies using hit information from 3-inch photomultiplier tubes (PMTs) and the OCCUPANCY method. Our algorithm demonstrates excellent performance in accurate energy reconstruction, validated with electron Monte Carlo samples spanning kinetic energies from 10 MeV to 1 GeV.

Keywords: Energy reconstruction, Liquid scintillator detectors, JUNO, occupancy

Introduction

Liquid scintillator (LS) detectors are extensively used in nuclear and particle physics. Over the past few decades, LS detectors have played crucial roles in achieving remarkable scientific results in neutrino experiments [1–5]. The central detector (CD) of the Jiangmen Underground Neutrino Observatory (JUNO) will be the world's largest liquid scintillator detector, aiming to probe multiple physics goals including determining the neutrino mass ordering and accurately measuring neutrino oscillation parameters through reactor antineutrinos, as well as observing supernova neutrinos, solar neutrinos, atmospheric neutrinos, etc. [6]. JUNO has developed highly transparent LS and highly efficient PMTs with 78% photo coverage. These optimizations are necessary for JUNO to achieve the key requirements for determining the neutrino mass ordering, including an unprecedented energy resolution of $3\%/\sqrt{E(MeV)}$ and better than 1% energy scale uncertainty. Additionally, JUNO has developed a dual calorimetry technique [7, 8] that can not only calibrate the non-linearity of the charge response of 20-inch PMTs, but also enable the detector to operate over a larger dynamic energy range.

Efficient algorithms are necessary for the reconstruction of individual event energies in JUNO. For the energy region of inverse beta decay (IBD) from reactor neutrinos ($E_{vis} < 10$ MeV), JUNO has developed many robust reconstruction algorithms based on traditional methods [9–11] or machine learning technology [12, 13]. Events with visible energies larger than several hundred MeV in the detector are primarily from atmospheric neutrino interactions, and their energy and direction reconstructions have been well studied using both probabilistic unfolding methods [14, 15] and machine learning technology [16, 17] to assist in determining the neutrino mass ordering [18]. However, energy reconstruction in the mid-energy region (10 MeV $< E_{vis} <$ several hundred MeV), which includes events from the diffuse supernova neutrino background (DSNB) [19], Michel electrons, low-energy atmospheric neutrinos, and possible proton decays [20], is rarely discussed in previous studies.

The basic idea of current energy reconstruction algorithms in the JUNO central detector is based on either a data-driven maximum likelihood method or a machine learning strategy that utilizes information from the detector hit pattern. The data-driven maximum likelihood method has the advantage of better modeling the response of the real detector. It primarily utilizes the detector response to radioactive sources as calibration templates, with the energies of radioactive sources being in the MeV range [23]. However, it has been found that accurate energy reconstruction below 10 MeV can be affected by the spatial scale of energy deposition [11]. Therefore, it is necessary to investigate the feasibility and performance when applying this method to cases where events cannot be treated as point-like. We introduce the second moment S (Eq. 1) to describe the shape of both point-like and cluster-like events. This physical quantity is commonly used in accelerator experiments to describe the shape of clusters in energy calorimetry.

$$S = \frac{\sum_{\alpha=1}^{N_{\Delta E}} \Delta E_\alpha \times [\vec{r}_\alpha(x_\alpha, y_\alpha, z_\alpha) - \vec{r}(x,y,z)]^2}{\sum_{\alpha=1}^{N_{\Delta E}} \Delta E_\alpha}$$

where $N_{\Delta E}$ is the number of secondary energy depositions for the event, ΔE_α and $\vec{r}_\alpha(x_\alpha, y_\alpha, z_\alpha)$ are the energy deposition and position in the αth secondary energy deposition, respectively, and $\vec{r}(x,y,z)$ is the energy-deposit center for the event, which is the weighted average of secondary energy depositions and can be calculated as follows:

$$\vec{r}(x,y,z) = \frac{\sum_{\alpha=1}^{N_{\Delta E}} \vec{r}_\alpha(x_\alpha, y_\alpha, z_\alpha) \times \Delta E_\alpha}{\sum_{\alpha=1}^{N_{\Delta E}} \Delta E_\alpha}$$

Figure 1 [Figure 1: see original paper] compares the distributions of the second moment for electrons with different kinetic energies in JUNO's LS. As the kinetic energy of the electron increases, the distribution of the second moment becomes more diffuse, indicating a larger cluster of energy deposition. For comparison, Fig. 1 also shows the second moment distribution of muons with different energies deposited in the LS. The second moment distributions of cluster-like events and track-like events with the same energy deposition are very different, reflecting their shape differences in energy deposition. Moreover, for energy reconstruction of high-energy events, the potential deviation of PMT reconstructed charge (charge non-linearity) is also an important issue to consider.

The machine learning approach demonstrates good performance in event reconstruction as it can effectively utilize detector response information. However, it is important to note that this method relies on reliable data samples or simulation. The former requires reliable selection and data accumulation, while the latter usually needs adjustment according to real data, especially in the early stages of detector operation. Similar to the data-driven maximum likelihood method, since the PMT hit pattern is the basic input of machine learning, investigating the influence from potential charge non-linearity of PMTs based on real data is necessary.

In this paper, we investigate the energy reconstruction of events spanning from MeV to GeV in the JUNO CD using the data-driven maximum likelihood method [11]. To reduce dependence on the accuracy and non-linearity of PMT charge reconstruction, we utilize only information about PMT firing states (fired or unfired), known as the OCCUPANCY method. This paper focuses on the reconstruction of cluster-like events since the calibration templates in our study are constructed using point-like (or cluster-like) calibration sources. Thanks to studies of event identification in JUNO [14], we can effectively distinguish cluster-like events from track-like events. The reconstruction of track-like events (mainly muon-like events that have long tracks in the detector) is also an important topic and has been carried out in [14–17, 24–27]; however, it is not the subject of this article. To investigate the performance of our reconstruction, Monte Carlo (MC) simulation data generated by the JUNO offline software [28–30] is used for validation.

The details of our study are presented as follows: First, we introduce the JUNO detector and 3-inch PMT system (Sec. II). Then, we present the methodology of our reconstruction (Sec. III), including the construction of the calibration map and the maximum likelihood function. In Sec. IV, the reconstruction performance will be shown and compared. Finally, a summary will be provided in Sec. V.

II. JUNO Detector and 3-inch PMT System

As shown in Fig. 2 [Figure 2: see original paper], JUNO mainly consists of three sub-detectors: the CD, a water Cherenkov detector, and a top tracker detector [6, 31]. The CD contains 20 kilotons of LS in a 12 cm thick acrylic spherical container with a diameter of 35.4 m. The main component of the LS is linear alkylbenzene (LAB), with PPO (2,5-diphenyloxazole) as fluor and bis-MSB as wavelength shifter. A total of 17,612 20-inch PMTs (LPMTs) and 25,600 3-inch PMTs (SPMTs) will be installed on the exterior of the container as photosensors to collect photon signals. As a result, more than 1,345 photoelectrons (PEs) will be observed by the CD for a 1 MeV electron that fully deposits its kinetic energy in the LS. The SPMTs will work almost exclusively in single photoelectron (SPE) mode for reactor antineutrino detection (E_{vis} < 10 MeV). Therefore, SPMTs can serve as a linear reference for LPMTs and be used to calibrate the charge non-linearity of LPMTs. This feature is helpful in constraining some systematic uncertainties in LPMT energy reconstruction and improving the energy resolution. Moreover, SPMTs have the potential to detect supernova neutrinos and measure solar parameters ($_{12}$ and $\Delta m^2{}_{21}$) independently [32].

For detection of events with energies greater than tens of MeV or even GeV, most LPMTs will receive tens or even hundreds of PEs. For example, Fig. 3 Figure 3: see original paper shows the distribution of the number of PEs (nPE) received by LPMTs for a 500 MeV electron that deposits its kinetic energy in the LS. Obviously, all LPMTs are fired in this case. If the energy deposition occurs at the edge of the detector, nearby LPMTs will receive even more PEs.

The linearity of LPMT charge reconstruction over a large charge dynamic range is a challenge and needs to be calibrated and validated in the future. Based on experience from Daya Bay, an independent measurement system will be an effective solution [33, 34]. For comparison, in the same case of a 500 MeV electron depositing its kinetic energy in the LS, about 45%-60% of SPMTs are not triggered (Fig. 3(c)), and most fired SPMTs receive fewer than 5 PEs (Fig. 3(b)) due to their photocathode areas being about 40 times smaller. Therefore, we develop an energy reconstruction algorithm using only information from SPMTs. In addition, according to studies in [35, 36], the readout electronics of JUNO SPMTs may also exhibit non-linearity when receiving multiple hits. To minimize this effect, we use only firing information (fired or unfired). More details are introduced in Sec. III.

III. Method of Energy Reconstruction

A. Probabilities of SPMT Firing States

For each SPMT, the number of detected PEs obeys a Poisson distribution:

$$\text{Poisson}(k_i|\mu_i) = \frac{e^{-\mu_i}\mu_i^{k_i}}{k_i!}$$

where k_i is the nPE detected by the ith SPMT, and μ_i is the mean value of the Poisson distribution. As mentioned above, to reduce dependence on charge reconstruction accuracy, the OCCUPANCY method is applied which uses only information about SPMT firing states (fired or unfired). Therefore, only two states of k_i need to be considered: $k_i = 0$ (unfired) and $k_i > 0$ (fired). The probabilities of these two states can be described by Eq. 4 and Eq. 5 [21, 22]:

$$P_{\text{unfired}} = \text{Poisson}(k_i = 0|\mu_i) = e^{-\mu_i}$$

$$P_{\text{fired}} = \text{Poisson}(k_i > 0|\mu_i) = 1 - P_{\text{unfired}} = 1 - e^{-\mu_i}$$

In real detection, k_i will be smeared by fluctuations in photoelectron detection, while μ_i will be distorted due to additional contributions from PMT dark count. In addition, to avoid false triggering from electronic noise, we apply thresholds to each SPMT, which also affect μ_i. Typically, 0.3 PEs is chosen as the threshold since it can effectively handle electronic noise. Taking these effects into account, the probabilities of unfired and fired states are:

$$P_{\text{unfired}} = P(q_i < q_{\text{threshold}}|\mu_i^{\text{true}}) = \text{Poisson}(k_i = 0|\mu_i^{\text{true}}) + P_{\text{threLoss}}(\mu_i^{\text{true}})$$

$$P_{\text{fired}} = P(q_i \geq q_{\text{threshold}}|\mu_i^{\text{true}}) = 1 - P_{\text{unfired}}$$

where q_i is the reconstructed charge of the ith SPMT, $\mu_i^{\text{true}} = \mu_i^{\text{phy}} + \mu_i^{\text{dn}}$ is the mean value of the Poisson distribution, which consists of two components: (1) μ_i^{phy} caused by the visible energy of physics events; and (2) μ_i^{dn} introduced by the dark count (DR_i) of the ith SPMT, calculated by $\mu_i^{\text{dn}} = \text{DR}_i \times t$ in a time window of t. $P_{\text{threLoss}}(\mu_i^{\text{true}})$ is the probability of $q_i < q_{\text{threshold}}$ (0.3 PEs in this study) in the case of $k_i > 0$, calculated as follows:

$$P_{\text{threLoss}}(\mu_i^{\text{true}}) = \sum_{k_i=1}^{\infty} \left[\text{Poisson}(k_i|\mu_i^{\text{true}}) \times \int_{-\infty}^{q_{\text{threshold}}} \text{Gaus}(g_i, \sigma_{g_i})\, dq \right]$$

with $g_i = S_{\text{gain}} \times k_i$, $\sigma_{g_i} = g_i \times \sigma_{\text{spe}}$, where n indicates the case of multiple PEs, S_{gain} corresponds to the ratio between the real SPMT gain and the normal SPMT gain (3×10^6) in JUNO, and σ_{spe} denotes the SPE resolution of the ith SPMT. In real detection, S_{gain} and DR_i can be obtained from PMT calibration.

B. Construction of the Calibration Map

JUNO has designed a comprehensive calibration system [6] to understand the detector response, deploying multiple radioactive sources at various locations inside/outside the CD, including the Auto Calibration Unit (ACU), Cable Loop System (CLS), Guide Tube Calibration System (GTCS), and Remotely Operated Vehicle (ROV). Figure 4 [Figure 4: see original paper] shows the individual calibration systems in the CD and their scanning regions. For example, the ACU system scans the detector response along the central axis with multiple calibration sources, and the CLS system can scan in a two-dimensional plane (X-Z plane) with multiple calibration sources using the central cable and side cable. The strategy of the JUNO calibration system has been developed and optimized based on Monte Carlo simulation results [23].

In energy reconstruction, μ_i^{phy} directly corresponds to the visible energy of an event in the detector, which forms the basis of our method. Assuming a calibration source is loaded at location $\vec{r}(r, \theta, \phi = 0)$ in the central detector, the mean value of visible-energy-induced PEs for the ith SPMT is $\mu_i^{\text{phy, source}}$, which corresponds to the visible energy (denoted as E_{source}) of the calibration source. Then for an event depositing its energy at the same location, the relationship between the event's visible energy E_{vis} and μ_i^{phy} for the ith SPMT can be described as follows:

$$\frac{E_{\text{vis}}}{E_{\text{source}}} = \frac{\mu_i^{\text{phy}}}{\mu_i^{\text{phy, source}}}$$

It should be noted that μ_i^{phy} is related not only to the visible energy and position of the event, but also to the relative position (θ_{PMT}) between the event and the ith SPMT. This relationship can be determined using calibration data, which means constructing a calibration map. In Sec. III C, the maximum likelihood method will be adopted to reconstruct the visible energy by estimating μ_i^{phy} via the calibration map and invoking the firing states of 25,600 SPMTs from data. Next, we introduce the construction of the calibration map.

According to the calibration strategy in JUNO, this study uses the ^{68}Ge source ($E_{\text{source}} = 1.022$ MeV) to calibrate the X-Z plane with assistance from both ACU and CLS systems across 227 positions. Using the JUNO offline software [28–30], 10,000 ^{68}Ge events are generated for each calibration location on the X-Z calibration plane. Realistic detector geometry is employed for all samples, and the optical parameters of the LS are implemented based on precise measurements [37–43]. Comprehensive optical processes are simulated using Geant4 [44]. Furthermore, the official electronic simulation (including SPMT charge smearing, transit time spread, and dark noise, etc., referenced from measurements in [45]) and charge reconstruction are also applied in this study.

In calibration, when the ^{68}Ge source is loaded at one of the 227 planned locations, the probability of the unfired state for the ith SPMT can be estimated by Eq. 9, where $N_{q_i<q_{\text{threshold}}}$ corresponds to the number of events with $q_i < q_{\text{threshold}}$, and N_{total} is the total number of events for the calibration sample (in this study $N_{\text{total}} = 10,000$). According to Eq. 6, for convenience we use an effective mean value of detected PEs ($\mu_i^{\text{det, source}}$) in Eq. 10. Then $\mu_i^{\text{det, source}}$ can be estimated by Eq. 11 using the calibration data. Obviously, this calculation requires that the ith SPMT is not fired for all 10,000 events in the calibration sample (^{68}Ge); otherwise this method is no longer applicable. Due to the small visible energy of ^{68}Ge and the fact that even the most marginal of the 227 calibration positions is about 2 meters away from its neighboring SPMTs, this extreme scenario is extremely unlikely.

$$P_{\text{unfired}} = P(q_i < q_{\text{threshold}} | \mu_i^{\text{true, source}}) = \frac{N_{q_i<q_{\text{threshold}}}}{N_{\text{total}}}$$

$$P_{\text{unfired}} = \text{Poisson}(k_i = 0 | \mu_i^{\text{det, source}}) = e^{-\mu_i^{\text{det, source}}}$$

$$\mu_i^{\text{det, source}} = -\ln P_{\text{unfired}} = -\ln\left(\frac{N_{q_i<q_{\text{threshold}}}}{N_{\text{total}}}\right)$$

It should be noted that $\mu_i^{\text{phy, source}}$ is the value required for energy reconstruction (Eq. 8), while $\mu_i^{\text{det, source}}$ includes contributions from visible energy, PMT dark count, charge smearing, and threshold effects. According to Eq. 6, Eq. 10, σ_{spe}, and PMT parameters (S_{gain} and DR_i) from PMT calibration, we can find the relationship between $\mu_i^{\text{phy, source}}$ and $\mu_i^{\text{det, source}}$. Figure 5 [Figure 5: see original paper] shows an example for an SPMT with SPE resolution and dark count rate of 30% and 1 kHz, respectively, and a readout window of 1000 ns. Dark counts dominate $\mu_i^{\text{det, source}}$ for small $\mu_i^{\text{phy, source}}$, while the combined effect of dark count, smearing, and threshold remains stable at around 2% for the given setting as $\mu_i^{\text{phy, source}}$ increases.

Considering that the CD has good symmetry and SPMTs with the same relative position with respect to the calibration source exhibit similar responses, to enhance accuracy we further group and combine SPMTs with similar θ_{PMT} values in the calculation of $\mu_i^{\text{phy, source}}$. In this work, θ_{PMT} is divided into 1,440 groups from 0° to 180°, with 0.125° per group. The same approach has been successfully verified and applied in [23]. As a result, for each ^{68}Ge source location $\vec{r}(r,\theta,\phi=0)$, SPMTs in the same θ_{PMT} group have similar values of $\mu_i^{\text{phy, source}}$, the average of which is denoted as $\mu^{\text{phy, source}}(\vec{r},\theta_{\text{PMT}})$. The calibration map can be constructed after ^{68}Ge scans 227 locations on the X-Z plane and all $\mu^{\text{phy, source}}(\vec{r},\theta_{\text{PMT}})$ values are calculated. Considering calibration performance and time consumption in JUNO, only about 227 calibration points are available in the current calibration strategy, so interpolation is necessary for remaining positions. Figure 6 Figure 6: see original paper and Fig. 6(b) show examples of the calibration map before and after interpolation, respectively.

The following is a brief summary of the main steps in constructing the calibration map: 1. For ^{68}Ge loading at location $\vec{r}(r,\theta,\phi=0)$, calculate the effective mean value of detected PEs ($\mu_i^{\text{det, source}}$) for each SPMT using Eq. 11; 2. Calculate $\mu_i^{\text{phy, source}}$ by correcting for PMT dark counts and threshold effects; 3. Calculate $\mu^{\text{phy, source}}(\vec{r},\theta_{\text{PMT}})$, which is the average value of $\mu_i^{\text{phy, source}}$ for each θ_{PMT} group; 4. Repeat the above steps for calibration data at all locations; 5. Apply interpolation to remaining positions; 6. For a given ^{68}Ge location $\vec{r}(r,\theta,\phi=0)$, the $\mu^{\text{phy, source}}(\vec{r},\theta_{\text{PMT}})$ value corresponding to each SPMT can be obtained.

The calibration map is generated using calibration data on the X-Z plane ($\phi=0$) by considering that the detector exhibits good symmetry along the ϕ direction. According to a detailed study in [23], the ϕ symmetry is reliable for events located within 16 m, while ϕ dependence cannot be ignored for regions near the edge. In the future, ϕ symmetry needs to be checked and validated using real data, and can be corrected if necessary.

C. Construction of Maximum Likelihood Function

To reconstruct the visible energy of a cluster-like event whose energy-deposit center is known in the detector, a likelihood function can be constructed as follows:

$$L(E_{\text{vis}}) = \prod_{i=1}^{N_{\text{unfired}}} P_{\text{unfired}} \times \prod_{i=1}^{N_{\text{fired}}} P_{\text{fired}}$$

where $N = N_{\text{unfired}} + N_{\text{fired}} = 25,600$, N_{unfired} and N_{fired} correspond to the number of SPMTs with $q_i < 0.3$ PEs and $q_i \geq 0.3$ PEs, respectively. P_{unfired} and

P_{fired} are the probabilities of unfired and fired states, which can be calculated using Eq. 6, respectively.

In the calculation, μ_i^{phy} for each SPMT can be estimated by considering the relationship in Eq. 8 and invoking the $\mu^{\text{phy, source}}(\vec{r}, \theta_{\text{PMT}})$ value from the calibration map. In addition, differences in quantum efficiency (QE) between individual SPMTs in the same θ_{PMT} group should be considered. As a result, μ_i^{phy} needs a correction and can be calculated as follows:

$$\mu_i^{\text{phy}} = \frac{\text{QE}_i}{\frac{1}{m}\sum_{j=0}^{m}\text{QE}_j} \times \mu^{\text{phy, source}}(\vec{r}, \theta_{\text{PMT}})$$

where QE_i is the QE of the ith SPMT, m is the number of SPMTs in the θ_{PMT} group classified by the θ_{PMT} value, and QE_j is the QE of the jth SPMT in this group.

Next, ROOT's minimization class TMinuit [46, 47] is used for minimizing $-\ln L$. In minimization, the visible energy E_{vis} of the cluster-like event (whose energy-deposit center is known and will be introduced in Sec. IV A) is the parameter to be determined, and its initial value (E_{initial}) can be estimated as Eq. 14 using the total number of PEs (totalPE) from all SPMTs to reduce reconstruction time. $\text{totalPE}_{\text{source}}(r)$ is the totalPE observed by 25,600 SPMTs for the ^{68}Ge source located at different positions (Fig. ??). Comparing $\text{totalPE}_{\text{source}}(r)$ at the center of the CD and at $r \approx 15$ m, there is about 7% non-uniformity introduced by PMT reception and optical attenuation during photon transmission. The decrease for radii larger than \$ \$15.6 m is mainly caused by total reflection and shadowing effects.

$$E_{\text{initial}} = \frac{\text{totalPE}(r)}{\text{totalPE}_{\text{source}}(r)} \times E_{\text{source}}$$

After minimization, TMinuit returns the predicted visible energy value as the result of energy reconstruction. Furthermore, the response difference caused by the spatial scale of energy deposition is investigated in Sec. III D, where it is found to have little influence on our analysis.

D. Comparison of Cluster-like and Point-like Events

^{68}Ge is a positron source. The positron annihilates in the source capsule (stainless steel + PTFE) with a pair of 0.511 MeV γ rays emitted. Most of the γ ray energy is deposited within \$ \$30 cm in the LS, so ^{68}Ge is not strictly a point-like source but a cluster-like source similar to the high-energy electrons described earlier in Sec. I. In this paper, to determine location-dependent $\mu^{\text{phy, source}}$ from calibration data and perform energy reconstruction, we construct a calibration map using the approximate point-like ^{68}Ge source (cluster size \$ \$30 cm).

For energy reconstruction of high-energy electrons with larger cluster sizes (several meters), considering that their energies are deposited in a relatively symmetrical LS volume without (or with little) distortion caused by energy leakage, and the centers of their energy depositions similarly coincide with their locations, the calibration map is expected to be applicable by assuming all energy deposition occurs at the energy-deposit center. However, this assumption and simplified treatment may introduce bias in energy reconstruction, so we need to investigate the response difference caused by the spatial scale of energy deposition for high-energy events.

According to Eq. 8, for an event with known position in the LS, with E_{source} and $\mu^{\text{phy, source}}$ obtained from the calibration map, the sum of all SPMT μ_i^{phy} values is directly proportional to the visible energy of the event, as shown in Eq. 15. Therefore, any bias present in the sum of all SPMT μ_i^{phy} values indicates deviation of the visible energy.

$$\sum_{i=1}^{N} \mu_i^{\text{phy}} = \frac{E_{\text{vis}}}{E_{\text{source}}} \times \sum_{i=1}^{N} \mu_i^{\text{phy, source}}$$

In energy reconstruction, our algorithm assumes all energy deposition occurs at the energy-deposit center. However, in real detection, μ_i^{phy} of the ith SPMT is contributed by the cumulative effect of each secondary energy deposition. To estimate potential bias caused by the spatial scale of energy deposition for high-energy events, the sum of all SPMT μ_i^{phy} values (Eq. 15) is calculated using different strategies. As shown in Eq. 16 and Eq. 17, they are calculated as point-like and cluster-like events, respectively:

$$\sum_{i=1}^{N} \mu_i^{\text{phy}}|_{\text{point-like}} = \frac{E_{\text{vis}}}{E_{\text{source}}} \times \sum_{i=1}^{N} \mu_i^{\text{phy, source}}(\vec{r})$$

$$\sum_{i=1}^{N} \mu_i^{\text{phy}}|_{\text{cluster-like}} = \frac{E_{\text{vis}}}{E_{\text{source}}} \times \sum_{\alpha=1}^{N_{\Delta E}} \Delta E_\alpha \times \sum_{i=1}^{N} \mu_i^{\text{phy, source}}(\vec{r}_\alpha)$$

The official JUNO simulation software is applied to generate electron samples with different kinetic energies, and the details of energy deposition (ΔE_α and $\vec{r}_\alpha$) are recorded for calculation of Eq. 16 and Eq. 17. We compare the calculation results as shown in Eq. 18 and Fig. 7 [Figure 7: see original paper]. It was found that the ratio is close to 1 with increasing R^3, and it has a small bias ($\leq$ 0.5%) at the edge for electrons with kinetic energies larger than 200 MeV. This result indicates that our algorithm and reconstruction strategy are applicable to energy reconstruction of high-energy events with large spatial scales of energy deposition.

$$\text{Ratio} = \frac{\sum_{i=1}^{N} \mu_i^{\text{phy}}|_{\text{cluster-like}}}{\sum_{i=1}^{N} \mu_i^{\text{phy}}|_{\text{point-like}}}$$

IV. Reconstruction Results

In this section, the JUNO offline software is used to simulate electrons uniformly distributed in the CD with kinetic energies of 10, 20, 50, 100, 200, 350, 500, 700, 1000, and 2000 MeV as MC samples to validate the reconstruction algorithm. The MC samples are generated with full-chain simulation in JUNO including realistic detector geometry, comprehensive physical and optical processes, official electronic simulation, and charge reconstruction. A 16 m radius cut is applied to avoid energy leakage for high-energy events and the total reflection effect at the detector edge. Finally, there are about 10,000 events for each electron sample.

A. Reconstruction of Energy-Deposit Center

As introduced in Sec. III C, the event's energy-deposit center is required to reconstruct the visible energy. Therefore, before energy reconstruction, it is necessary to reconstruct the energy-deposit center. Compared to vertex reconstruction of point-like events, energy-deposit center reconstruction of high-energy cluster-like events faces greater dispersion (Sec. I). After investigation, we find that the time-based algorithm developed and verified in [48] is suitable and can be applied in our analysis.

The time-based algorithm uses the distribution of time-of-flight (TOF) corrected time Δt (Eq. 19) of an event to reconstruct its vertex and t_0 (event time). The principle of the time-based algorithm is that the Δt distribution is independent of the event vertex after applying the time-of-flight correction. In this paper, we apply it to reconstruct the energy-deposit center.

$$\Delta t_i = t_i - t_{\text{ofi}}$$

In Eq. 19, t_i is the first hit time of the ith SPMT and t_{ofi} is the time of flight from the energy-deposit center to the ith SPMT. In calculating t_{ofi}, the optical path length includes both the length in the LS and in the water. A correction vector is then constructed and minimized by iterating the energy-deposit center. More details can be found in [48]. The reconstructed energy-deposit center can be obtained, and Fig. 8 and Fig. 9 [Figure 9: see original paper] show the performance. The reconstruction biases of θ (Fig. 8 Figure 8: see original paper) and ϕ (Fig. 8(c)) remain small and stable as energy increases, while the reconstruction bias of R (Fig. 8(a)) gradually increases with energy. However, it can still be controlled within 150 mm at 1 GeV. Considering that the cluster size could be several meters for a 1 GeV electron, this bias is acceptable. The effect of this deviation on energy reconstruction will be discussed later. On the other hand, the reconstruction bias of R tends to decrease at the edge of the detector compared to other regions, mainly due to energy leakage near the edge, especially for high-energy events.

In Fig. 9, we find that the reconstruction resolutions of R, θ, and ϕ increase with electron energy between 50 MeV and 1 GeV. For example, the resolutions of R, θ, and ϕ are about 100 mm, 0.5°, and 1.0° for 50 MeV electrons, respectively, while they are about 340 mm, 1.8°, and 3.0° for 1 GeV electrons, respectively. This effect is mainly due to greater dispersion of energy deposition for high-energy electrons. The resolutions for 10 MeV electrons are slightly larger than for 50 MeV electrons because the number of hit SPMTs is small ($ $400 PEs for 10 MeV), providing less information for reconstruction using the time-based algorithm.

B. Energy Reconstruction Performance

Next, we introduce the performance of energy reconstruction. The reconstructed energy spectra for electrons with different kinetic energies are shown in Fig. 10 [Figure 10: see original paper]. The blue spectra correspond to events whose energies are fully contained (FC) in the LS, while the green spectra correspond to events whose energies are partially contained (PC). For electrons with energies greater than 500 MeV, the proportion of PC events becomes larger and the 16 m cut cannot totally exclude energy leakage. The FC spectra can be well-fitted with a Gaussian function, and the reconstructed energy is about 6% larger than the deposited electron energy. According to the official JUNO simulation, when anchored at the 2.223 MeV gamma peak generated by (n,γ)H, high-energy electrons have an energy non-linearity of $ $6% [49]. Thus, this deviation is understood and is mainly caused by the non-linear energy response of the LS.

On the other hand, non-uniformity of energy reconstruction may also introduce some small deviations, but generally less than 1%, as shown in Fig. 11(c). To understand the non-uniformity shown in Fig. 11(c), Fig. 11(a) and Fig. 11(b) can be compared, corresponding to cases using the true energy-deposit center without and with electronic simulation and charge reconstruction. In Fig. 11(a), for electron samples with different energies, the non-uniformity is consistent at about 0.5% from the detector center to the edge. After electronics simulation and charge reconstruction (Fig. 11(b)), there is a slight increase in non-uniformity, but it remains within 1.5%. Fig. 11(c) corresponds to the case using the reconstructed energy-deposit center, which shows deviation (Fig. 8). As a result, for 500 MeV and 1 GeV electrons, their energy non-uniformity is about 2% and 3% at the edge, respectively. Furthermore, if PC events are included (Fig. 12 [Figure 12: see original paper]), they mainly affect the non-uniformity of high-energy electrons located in the edge region.

Figure 13 [Figure 13: see original paper] shows the energy resolution performance. The solid points correspond to reconstruction results for FC events, while hollow points include both FC and PC events. The red squares and pink stars denote cases using the true energy-deposit center for energy reconstruction, while the green triangles use the reconstructed energy-deposit center. Electronics simulation and charge reconstruction are applied for the pink stars and green triangles. Comparing energy resolutions under different conditions, we find that the energy reconstruction performance for high-energy events is good using the OCCUPANCY strategy, with energy resolution of about 0.8% for 1 GeV electrons in the ideal case (red solid squares). For a more realistic situation including electronic simulation and charge reconstruction, the resolution is only about 0.3% worse, indicating that the correction works well in controlling the influence from PMT dark count and threshold effects. Comparing solid and hollow points, PC events mainly affect electrons with kinetic energies larger than 100 MeV, deteriorating their energy resolutions by about 1%. In real detection, the reconstructed energy-deposit center is required for energy reconstruction, and its smearing introduces additional smearing on the reconstructed energy, especially for high-energy electrons. As a result, the energy resolution is about 3.2% for 1 GeV electrons based on our algorithm.

In Fig. 14 [Figure 14: see original paper], the relationship between energy resolution and the fired ratio of SPMTs is investigated using electron samples without electronics simulation, with the true energy-deposit center applied. In general, a higher fired SPMT ratio corresponds to better energy resolution. This indicates that our algorithm has potential for application to higher-energy events when the fired SPMT ratio is not close to 1, provided we can solve the problem of energy-deposit center reconstruction which has larger bias at higher energies.

V. Summary

Accurate energy reconstruction is crucial for detecting various physics events across a wide energy range from MeV to GeV in JUNO. This work focuses on energy reconstruction of sub-GeV events based on 3-inch PMTs and the OCCUPANCY method. Our reconstruction shows good performance in tests with MC simulation samples. The energy non-uniformity can be controlled within 1% from the detector center to the edge for electrons with kinetic energies below 500 MeV. For 1 GeV electrons, the energy non-uniformity can be controlled within 3%. The energy resolutions for 1 GeV electron FC events and FC+PC events are about 2.7% and 3.2%, respectively. Our algorithm has the advantage of minimal dependency on precise charge reconstruction by primarily using information from SPMT firing states.

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