Reconstruction based on Self-calibration in liquid scintillator detectors

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Abstract

1 Introduction

1.1 Calibration of scintillator detector may bring extra challenges

1.1.1 The advantages of scintillator detector

Scintillator is a good candidate for neutrino observation for its better energy resolution and low energy threshold. However, to calibrate a scintillation detector is a hard work.

1.1.2 Why calibration is so difficult

1. The calibration source need high purity, which adds high difficulties to the mechanical process and demand high cost. 2. It is hard to fix calibrate source in the detector, which may cause extra accident, either. 3. The structure of the calibration source may bring shadows which is different to the real situation, requiring more correction in simulation.

1.1.3 The objective of this paper is to reconstruct with no calibration detector

1. We try to reconstruct the vertex and unknown structures if we have plenty of data without calibration. 2. If calibration is done, a cross check can be applied to reduce the error in measurement.

1.2 The importance of reconstruction

1.2.1 Why reconstruction is so important?

Reconstruction is necessary for reduce the background caused by PMT and supporting structures , raise the energy resolution and identify the particle type.

1.2.2 Who else has done that?

1.Traditional reconstruction is a likelihood or divide detectors into many segment bins, such as Daya Bay. (How to reconstruct resolution by Borexino, SNO+, Daya Bay)

2. Machine learning has broadly applied in current physical experiments, such as neural networks. 3. EM algorithm is useful in estimating the unknown distribution. and been widely used in many aspects.

1.3 Highlight of this paper and purpose of this paper

This is the first series reconstruction without calibration. The main algorithm uses EM algorithm to reconstruct vertex and time profile. We use software JSAP based on ROOT system and GEANT4. and reconstruction.

Section 2 shows the how EM algorithm reconstruct vertex and time profile in different steps. and E-step and M-step is section 2.3.1 and 2.3.2. Section 3 shows the simulation condition and reconstruction result. Section 4 shows the conclusion and discussion.

2 EM Algorithms for Reconstruction

2.1 Using EM iteration to raise the resolution

2.1.1 How traditional EM algorithm update parameters

EM is useful in estimate unknown distribution. Each step maximize the likelihood use the parameters in last step.

$$\begin{cases} E-step: \tau^{[k+1]} = \arg\max_{\tau} L(\tau^{[k]}, \Theta^{[k]}; n_i, t_i) \\ M-step: \Theta^{[k+1]} = \arg\max_{\Theta} L(\tau^{[k+1]}, \Theta^{[k]}; n_i, t_i) \end{cases} \tag{2.1}$$

We use M-step find the vertex that maximize the likelihood , for E-step, we add a little correction to make the estimation of the time profile more physical. which will be detailed described in subsection 2.1.3

A flow chart to describe simplified EM process is shown in figure 1

2.2 Initial guess of the τ_0 and Θ_0

1. In 0-th iteration, we first use the pe information to estimate a rough result including the energy and vertex.

2. Initial guess of vertex and energy. We begin with the vertex using weighted average.

$$\vec{x}_{ini} = \frac{\sum_{i=1}^{N} n_i \vec{x}_i}{\sum_{i=1}^{N} n_i} \tag{2.2}$$

3. Initial guess of time profile Then using the time data reconstruct the time profile by

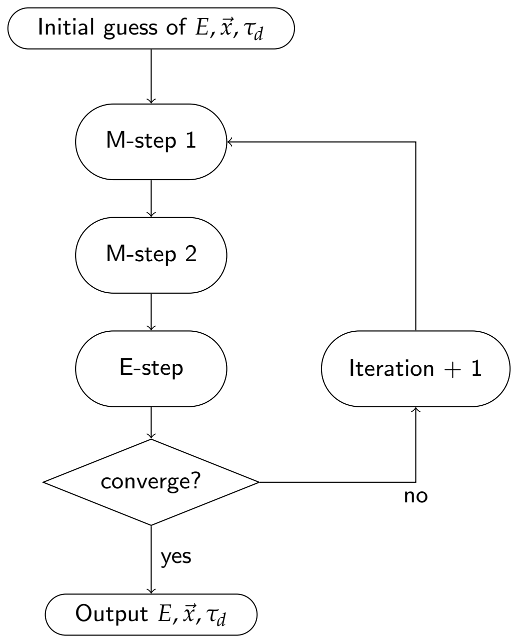


Figure 1: The flow chart of the reconstruction

$$p(t) = \frac{\tau_r + \tau_d}{\tau_d^2} \exp(-\frac{(t-t_0)}{\tau_d})(1 - \exp(-\frac{t-t_0}{\tau_r}))(t > t_0) \tag{2.3}$$

$$\tau_d = \arg_{\tau_d} \max \sum_i \log p_i(t) \tag{2.4}$$

2.3 M-step to find the best fit vertex and τ_d

2.3.1 Traditional algorithm based on charge information

Traditional reconstruction algorithm is applied in M-step. The likelihood function can be resolved into 2 parts

$$\log L\{\mathbf{x}, E; n_i, t_j\} = \log L\{\mathbf{x}, E; n_i\} + \log L\{\mathbf{x}, E; t_j\} \tag{2.5}$$

The former part only includes charge information and the latter includes time information readout by photosensors. The likelihood is to calculate the total probability of received photons by each PMT

$$p_i^* = \begin{cases} p_{i,s}\{\mathbf{x}, E\} p_{i,t}\{\mathbf{x}, S(t)\} & n_i > 0 \text{ (Fired PMT)} \\ p_{i,s}\{\mathbf{x}, E\} & n_i = 0 \text{ (Unfired PMT)} \end{cases} \tag{2.6}$$

$$\log L\{\mathbf{x}, E\} = \log \prod_i p_i^* = \sum_i \log p_{i,s}\{\mathbf{x}, E\} + \sum_{i'} \log p_{i',t}\{\mathbf{x}, S(t)\} \tag{2.7}$$

i is the index of all PMTs and i' only includes fired PMTs.

The combined likelihood includes vertex and unknown dependence, which will be reconstructed by maximize the likelihood, and we will derivate detailed form from abstract to a calculative one in the following section.

The number of photon electrons received by PMT is approximately a Poisson distribution.

$$p_i = \frac{\xi_i^{n_i}}{n_i!} \exp(-\xi_i) \tag{2.8}$$

To estimate the ξ_i, we need to consider the loss on propagation and photo coverage and photo response. The propagation mainly caused by attenuation is nearly an exponential decay. The photo coverage $\Omega_i(\mathbf{x})$ based on the occupancy of PMTs, while the vertex contributes to the solid angle . Finally, the photo response is the quantum efficiency η_{QE} of each PMT.

The expected photon on each PMT is also proportional to kinetic energy and light yield, therefore

$$\xi_i = E \cdot Y \cdot \exp(-\frac{d_i(\mathbf{x})}{L(\lambda)}) \cdot \frac{\Omega_i(\mathbf{x})}{4\pi} \cdot \eta_{i,QE}(\lambda) \tag{2.9}$$

Involving all the PMTs, the log likelihood is

$$\log L = \sum_{i=1}^{N} \log p_{i,s}\{\mathbf{x}, E; n_i\} \tag{2.10}$$

The simplified lifetime of a scintillator photon can be generalized in 4 steps (if no scattering):

1. At t_0, the particle at vertex $\mathbf{x}$ begin the travel like a point source.

2. The excited scintillator molecules emit photons with the deexcite time $t_{j,p}$ satisfy time profile distribution $p(t)$, if finally received by j-th PMT.

3. Photons flight to j-th PMT with flight time $t_{j,f}$ which is relative to the vertex.

$$t_{j,f}(\mathbf{x}) = \frac{|\mathbf{x}_j - \mathbf{x}|}{c/n(\lambda)} \tag{2.11}$$

4. Photons transmit in PMT satisfy a normal distribution with average transit time $t_{\mathbf{TT}}$ and transit time spread $t_{\mathbf{TTS}}$

Therefore, the time information of j-th fired PMT t_j include 4 parts.

$$t_0 + t_{j,p} + t_{j,f}(\mathbf{x}) + t_{\mathbf{TT}} + t_{\mathbf{TTS}} = t_j \tag{2.12}$$

Since t_0 and $t_{\mathbf{TTS}}$ are constant, The total uncertainty $U(t)$ is consist of time profile and TTS, the whole process is a convolution.

$$U(t) = p(t|\tau_d) \otimes t_{\mathbf{TTS}} \tag{2.13}$$

log likelihood of time:

$$\log L = \sum_{j=1}^{n} \log p_{j,t}\{\mathbf{x}; U(t), t_j\} \tag{2.14}$$

2.3.2 M-step to avoid local minimum and reconstruct τ_d

Since $U(t)$ is relative to τ_d and TTS, the distribution can be parameterized by reconstructing τ_d. τ_d is believed to determined by initial energy.

M-step plus utilize the result in M-step, in other words, the energy and vertex is known, but the unknown distribution such as decay time constant is fit as pending. We use log likelihood

$$\log L\{\tau|x, E\} = \log \prod_i p_i^* = \log p_{j,t}\{\mathbf{x}, t_j; S(t)\} \tag{2.15}$$

$$\tau = \arg_\tau \max\{\log L\{\tau\}\} \tag{2.16}$$

The best τ will be a fixed parameter in next E-step.

Since the analytical form of the uncertainty is quite complex, and the performance of the optimization do not play well in high dimension, we divided the likelihood into 2 parts. The comparison will be explained further in discussion.

2.4 E-step to shape the best fit unknown distribution and the added constraints

2.4.1 The problems encountered in traditional likelihood

However, we believe the τ is relative to energy E, which means the τ should have the same performance with the same energy$E$, indicate we must add a constraint to it, Using likelihood

$$\tau = \arg_\tau \max \sum_{sameE} logL\{\tau|E\}$$

but the energy always coupling with big uncertainty, lead to big difficulties to selected event, to simplified

2.4.2 The variant E-step using cluster

A cluster algorithm will be used in M-step to update parameters. Our cluster focus on the shape-dominated parameter $\tau(E)$ and energy E, see figure 2

step 1. Using projection of energy dimension in log scale, using a normal distribution fitting to find the point beyond 3 σ, and defined as β particle.

step 2. Using a linear fitting to these points, finding the residual less than $+1\sigma$.

step 3. Sort out the noise points beyond 3σ of rest points, by Gaussian fitting. Later classification is based on the minimum distance to the sorted points defined as the same class.

step 4. Repeat classification by kNN until converge.

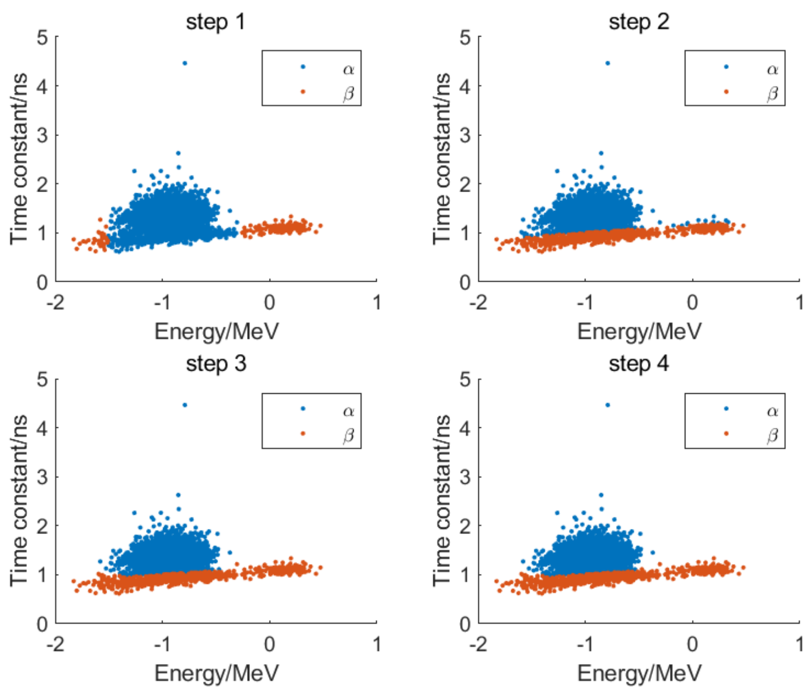


Figure 2: The process of how cluster works

3 Simulation and Result

3.1 Using JSAP Simulation to provide unlabled data

3.1.1 Introduction to JSAP

CJPL is located in Sichuan province with over 2000 meters, CJPL has the lowest cosmic rays and reactor neutrino flux background in the world JSAP use GEANT LAB + 0.07mg/L PPO and 13ug/L bis-MSB as the reaction material.

3.1.2 Introduction to the detector parameters(table1)

The detector radius, PMT response and other detail are shown in table 1. parameter of LS material: table 1

3.1.3 Introduction to the scintillator parameters

Scintillation photons are emitted when the molecule deexcite. and the time scaled by a double decay distribution.

Table 1: Simulation LS parameters

Parameters	value
Detector Radius	14.5 m
Transit time spread (TTS)	5.5 ns
Quantum efficiency	0.2
Attenuation length	$\sim$ 18 m
Light yield	4300/MeV

$$p(t) = \frac{\tau_r + \tau_d}{\tau_d^2} \exp(-\frac{t}{\tau_d})(1 - \exp(-\frac{t}{\tau_r})) \tag{3.1}$$

The decay time constant is relative to the energy, which is useful for energy reconstruction and particle identification. We set a log relationship of the decay time constant and energy.

Parameter of time profile, see figure 3

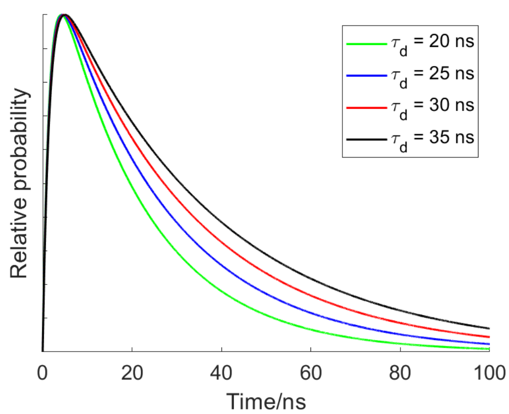


Figure 3: Time profile due to different τ_d

3.2 Unsupervised reconstruction result comparing to simulation truth information

3.2.1 How we plot our result and what info will be put on

1. The best $\Theta^{[k]}$ and $\tau^{[k]}$ will be found until converged.

2. We divided the detectors into many bins in 2-d to show the results.

3. The resolution is calculated by distance from reconstructed vertex to truth vertex

3.2.2 Describe the result by pictures

And describe the following picture in detail, each paragraph for a detailed description.

1. Performance of single class reconstruction

table1:

Table 2: Simulation LS parameters 0-th iteration

Uncertainty	sci	sci + che	sci + che + noise
0.2 MeV(center)/m	0	0	0
1 MeV(center)/m	0	0	0
2 MeV(center)/m	0	0	0

picture1: Resolution vs Energy and radius : At different position with energy, the reconstruction result will be ... see figure 4

picture2: Reconstruct time profile vs real profile : The reconstructed time profile comparing to the real profile will be ...

picture3: Resolution improvement with or without EM : The resolution changed with iteration will be... (0-th iteration is without EM) see figure 4(c) and figure 4(d)

2. Performance of double classes reconstruction

table 1:

Table 3: Simulation LS parameters 0-th iteration

Uncertainty	sci	sci + Che	sci + Che + noise
0.2 MeV(center)/m	0	0	0
1 MeV(center)/m	0	0	0
2 MeV(center)/m	0	0	0

picture1: Resolution vs Energy and radius : At different position with energy, the reconstruction result will be ...

picture2: Reconstructed time profile vs real profile : The reconstructed time profile comparing to the real profile will be ...

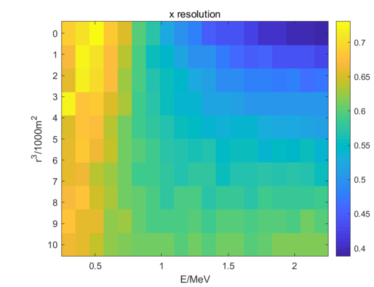
picture3: Resolution improvement with or without EM : The resolution changed with iteration will be... (0-th iteration is without EM)

3.3 Process the data

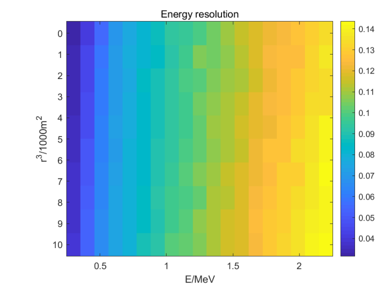
3.3.1 Particle identification

A cluster can applied to separate particles. The cluster is following the 4 steps.

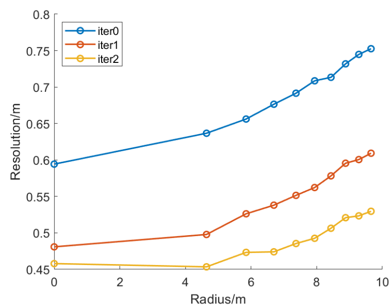
According to the result, the 2 particles can be classified by given the probability of each class. The error rate is then shown in table.



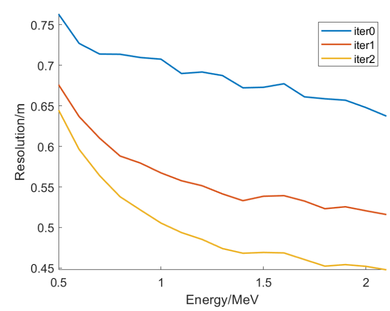
(a) pic1.



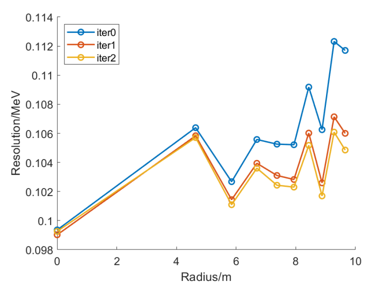
(b) pic2.



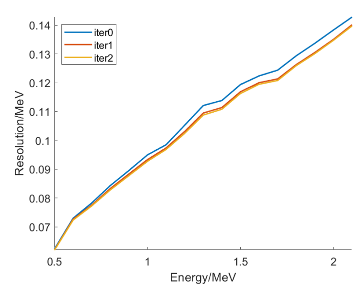
(c) pic3.



(d) pic4.



(e) pic5.



(f) pic6.

Figure 4: Reconstruction of energy and vertex

3.3.2 Energy dependent time profile

Decay time constant relative to energy can be plot by piece-wise function.

4 Conclusion and Discussion

4.1 Some impressive results in the picture

1. whether it is effective to single class reconstruction. 2. whether it is effective to double classes reconstruction 3. the performance comparing to the situation with noise or Cherenkov.

4.2 The reached resolution comparing to the traditional method

1. The reached resolution comparing to the theoretical. 2. The reached resolution comparing to the other experiment.

4.3 What can be done in the future

1. optics and geometry may be needed.

5 Appendix

5.1 Resolution derivation

5.2 Initial guess