Discrimination of pp solar neutrinos and 14C double pile-up events in a large-scale LS detector

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Abstract

As a unique probe, precision measurement of textit{pp} solar neutrinos is important for studying the Sun's energy mechanism, monitoring thermodynamic equilibrium, and studying neutrino oscillation in the vacuum-dominated region. For a large-scale liquid scintillator detector, one bottleneck for textit{pp} solar neutrino detection comes from pile-up events of intrinsic ^{14}C decays. This paper presents a few approaches to discriminate textit{pp} solar neutrinos and ^{14}C pile-up events by considering the difference in their time and spatial distributions. In this work, a Geant4-based Monte Carlo simulation is constructed. Then multivariate analysis and deep learning technology were adopted respectively to investigate the capability of ^{14}C pile-up reduction. As a result, the BDTG model and VGG network showed good performance in discriminating textit{pp} solar neutrinos and ^{14}C double pile-up events. hl{At the ^{14}C concentration assumption $5times10^{-18}g/g,$} their signal significance can achieve 10.3 and 15.6 using only one day of statistics. In this case, the signal efficiency is 51.1 % for discrimination using the BDTG model when rejecting 99.18 % ^{14}C double pile-up events, and the signal efficiency is 42.7 % for the case using the VGG network when rejecting 99.81 % ^{14}C double pile-up events.

Full Text

Preamble

Discrimination of pp solar neutrinos and ^{14}C double pile-up events in a large-scale LS detector

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Precision measurement of pp solar neutrinos serves as a unique probe for studying the Sun's energy generation mechanism, enabling monitoring of thermodynamic equilibrium and investigation of neutrino oscillations in the vacuum-dominated region. For large-scale liquid scintillator detectors, a critical bottleneck for pp solar neutrino detection is the pile-up events from intrinsic ^{14}C decay. This paper presents several approaches to discriminating between pp solar neutrinos and ^{14}C pile-up events by exploiting differences in their temporal and spatial distributions.

In this study, we conduct a Geant4-based Monte Carlo simulation and employ multivariate analysis and deep learning techniques to investigate the capability of ^{14}C pile-up reduction. The BDTG model and VGG network demonstrate excellent performance in discriminating pp solar neutrinos from ^{14}C double-pile-up events. Assuming a ^{14}C concentration of 5×10^{-18} g/g, the signal significance can reach 10.3 and 15.6 using statistics from only one day. For the BDTG model, the signal efficiency is 51.1% while rejecting 99.18% of ^{14}C double pile-up events. For the VGG network, the signal efficiency is 42.7% while rejecting 99.81% of ^{14}C double pile-up events.

Keywords: Liquid scintillator detector, pp solar neutrinos, ^{14}C pile-up, Multivariate analysis, Deep learning

Introduction

With advances in nuclear physics and astrophysics, we have gained insight into the Sun's energy mechanism, which originates from nuclear fusion of light nuclei in the solar core [1–3]. The proton-proton (pp) cycle produces approximately 99% of solar energy, with its primary reaction being the fusion of two protons into a deuteron: $p + p \rightarrow {}^{2}\mathrm{H} + e^{+} +$. This reaction emits large numbers of low-energy neutrinos, called pp neutrinos ($E < 0.42$ MeV). Additionally, the proton-electron-proton (pep) process and secondary reactions in the pp cycle produce pep neutrinos, ^{7}Be neutrinos, ^{8}B neutrinos, and hep (helium-proton) neutrinos. The remaining solar energy is contributed by the carbon-nitrogen-oxygen (CNO) cycle, which emits CNO neutrinos. Solar neutrino detection provides a direct test of theoretical solar models, but early observations revealed discrepancies with theoretical predictions [4–13], leading to the "solar neutrino problem" that persisted for over 30 years. Subsequently, the MSW-LMA mechanism [14,15] was established as the standard solution based on solid evidence from SNO [16,17] and KamLAND [18]. Currently, the standard solar model (SSM) [19–24] provides precise predictions of solar neutrino fluxes and energy distributions. Nearly all solar neutrino components have been observed [25–28], and we anticipate entering an era of precise and comprehensive solar neutrino measurements in the coming decades [29,30].

pp neutrinos are intimately connected to the Sun's dominant energy production mechanism and carry recent information from the solar core, making them crucial for studying the Sun's energy generation and monitoring thermodynamic equilibrium. Furthermore, pp neutrinos enable studies of neutrino oscillations in vacuum-dominated regions. Their detection requires both a low threshold (200 keV) and effective background reduction. pp neutrinos were first detected using ^{71}Ga-based radiochemical detectors [6–11], and subsequently, the Borexino experiment successfully applied a large-scale liquid scintillator (LS) detector to provide the best measurement of pp neutrinos at the 10% level [26,27] via elastic neutrino-electron scattering.

Based on experience from Borexino, intrinsic ^{14}C decays from organic liquid scintillator and their associated pile-up events constitute a critical internal background for large-scale LS detectors. ^{14}C pile-up events occur when more than one ^{14}C decay takes place at different detector positions within the same trigger window. These pile-ups can be classified by the multiplicity of ^{14}C accidental coincidences: double pile-ups, threefold pile-ups, and fourfold pile-ups. The Borexino experiment (278 ton) required considerable effort in LS purification to achieve a ^{14}C concentration of approximately 2.7×10^{-18} g/g. At this concentration, ^{14}C double pile-up accounts for approximately 10% of events in the spectral gap between the ^{14}C and ^{210}Po spectra [26].

For an LS detector with a sensitive target mass of m kilotons (kton), the frequency of a ^{14}C single event is given by:

$$f_{\text{single}}[\text{Hz}] = \frac{C_{^{14}\text{C}} \cdot N_A \cdot m}{\tau \cdot M} \times 10^9$$

where N_A is Avogadro's constant (6.023×10^{23}), and τ, M, and $C_{^{14}\text{C}}$ correspond to the ^{14}C lifetime, molar mass, and its concentration in the LS, respectively.

The frequency of ^{14}C pile-up events can be calculated as:

$$f_{\text{pile-up}}[\text{Hz}] = \frac{e^{-f_{\text{single}} \cdot \Delta t}}{(n-1)!} \cdot f_{\text{single}}^{n} \cdot \Delta t^{n-1} \cdot \varepsilon$$

where n (n $\geq$ 2) denotes the multiplicity of the ^{14}C accidental coincidence (e.g., n = 2 represents double ^{14}C pile-up), Δt is the detection time window, and corresponds to the reconstruction efficiency of ^{14}C pile-up events.

As detector mass increases, the dramatic rise in ^{14}C pile-up events must be considered and effectively rejected. Taking a large spherical LS detector with a 15 m radius and approximately 12 kton mass as an example, Table 1 lists the event rates for pp neutrinos and ^{14}C single and pile-up events at different ^{14}C concentrations. This calculation used a 500 ns time window and assumed

100% reconstruction efficiency. For a ^{14}C concentration of 5×10^{-18} g/g in the LS, Fig. 1 [Figure 1: see original paper] shows the recoil energy spectra of pp neutrinos via elastic neutrino-electron scattering (from [30]), compared with the energy spectra of ^{14}C single, double, and triple pile-up events. In this massive detector, ^{14}C pile-up events outnumber pp neutrino signals by more than two orders of magnitude.

The values in brackets in Table 1 indicate event rates within the energy range of interest (0.16–0.25 MeV) for deposited energy, considering that the Q-value of ^{14}C β decay is 156 keV and the scattered electron from pp neutrino reactions is difficult to distinguish from the emitted electron of a ^{14}C single event. The target mass of this detector (12 kton) is 43 times larger than Borexino (278 ton). Consequently, the signal-to-background ratio of pp neutrinos to ^{14}C double pile-up events is smaller than 1:126 for a ^{14}C concentration of 2.7×10^{-18} g/g, and becomes even lower at higher ^{14}C concentrations. However, energy resolution smearing requires the analysis energy range to be determined based on realistic conditions.

Several neutrino experiments are underway or planned, many of which [31–35] show good potential for pp neutrino detection due to their large detector targets, well-controlled radioactivity, low detection thresholds, or good energy resolution. However, in experiments with LS detectors of tens of kilotons, low-energy neutrino detection is challenging due to ^{14}C pile-up. Therefore, an approach for ^{14}C pile-up discrimination and reduction must be developed, particularly for ^{14}C double pile-up, as its event rate is much higher than other accidental coincidences.

This study focuses on discriminating between pp solar neutrinos and ^{14}C double pile-up events. While discrimination of other accidental coincidences with ^{14}C multiplicity ≥ 3 is important at higher ^{14}C concentrations, it is not addressed here. Our work proceeds as follows: First, we simulate an LS detector and investigate the PMT hit pattern features for pp neutrinos and ^{14}C double pile-up events (Sec. II). We then present several approaches for ^{14}C double-pile-up discrimination based on multivariate analysis and deep learning technology (Sec. III). Sec. IV shows and compares discrimination performances. Finally, Sec. V presents a summary.

II. Detector Simulation

In this study, a spherical LS detector was built using Monte Carlo (MC) simulations with the Geant4 toolkit [36] version 4.10.p02. The spherical detector had a 15 m radius, with LS contained in an acrylic sphere with 10-cm-thick walls. To simplify the simulation, a sensitive optical surface was defined for photon detection instead of detailed PMT simulation. This sensitive optical surface was a sphere outside the acrylic sphere, separated by a 1-m-thick water layer, allowing easy tuning of photosensor coverage and quantum efficiency.

In the simulation, the coverage rate was 65%, corresponding to approximately

10,650 twenty-inch photomultipliers (PMTs) uniformly distributed on the sensitive optical surface. Fig. 2 [Figure 2: see original paper] shows a schematic of the detector. An average quantum efficiency of 30% was used for the 20-inch PMTs with a 2% Gaussian relative spread. LS properties were referenced from [37–44], and comprehensive optical processes were adopted, including quenching, Rayleigh scattering, absorption, reemission, photon transport in the LS, and reflections on the acrylic surface. Table 2 summarizes the main PMT parameters, including transit time spread (TTS), quantum efficiency (QE), dark noise (DR), and single photoelectron (spe) resolution.

Consequently, approximately 1,100 photoelectrons (PEs) could be observed by the 10,650 PMTs for a 1 MeV electron fully depositing its kinetic energy at the detector center, corresponding to approximately 3% energy resolution. In contrast, approximately 106.5 additional PEs from PMT dark noise could be detected in a 500 ns time window.

To investigate the response features of pp neutrinos and ^{14}C double-pile-up events, MC samples were generated and compared. Approximately one million final-state electrons from pp neutrino elastic scattering were uniformly simulated in the LS volume, with the scattered electron spectrum referenced from [30]. Since final-state electrons from elastic scattering are similar to electrons emitted in ^{14}C β decay (^{14}C single events), distinguishing them on an event-by-event basis is difficult, requiring energy reduction to focus on a narrow energy region. We applied the same treatment method as Borexino. However, electrons with 200 keV kinetic energy in LS exhibit 5% energy nonlinearity [44,45], and energy resolution was included in the simulation. Therefore, our analysis applied a 270 PE cut to the total number of PEs from all PMTs, considering the 156 keV endpoint energy of ^{14}C β decay (163 PEs) and PMT dark noise contribution (106.5 PEs).

After the total PE cut, an MC sample of 100,000 pp neutrinos uniformly distributed in the LS was used for discrimination studies. To generate the ^{14}C double pile-up sample, we first produced a large dataset by simulating 10 million ^{14}C single events in the LS using ^{14}C β decay. Next, two ^{14}C single events were randomly selected and merged into a double-pile-up event. Since the ^{14}C lifetime exceeds 8000 years, the time interval between two ^{14}C single events can be considered uniformly distributed over a few hundred nanoseconds. Similarly, after applying a 270 PE cut, 100,000 ^{14}C double pile-up events were used for analysis.

As illustrated in Figs. 3 and 4, pp solar neutrinos and ^{14}C double pile-up events exhibit different features in their temporal and spatial distributions. pp solar neutrinos are single point-like events with energy deposition occurring in a relatively short time and small space, producing only one cluster in their PMT hit pattern. For ^{14}C double-pile-up events, if two ^{14}C atoms decay at different detector positions, two clusters are expected. However, since the hit time distribution of fired PMTs includes scintillation time, photon time-of-flight, and ^{14}C decay time, the hit time distribution is valuable for identification. In particular, when two ^{14}C atoms decay near each other, their spatial distribution may not differ significantly from a single point-like event, but the hit time distribution remains helpful if the time interval between decays is large, as shown in Fig. 4.

Our approach employs a straightforward trigger strategy that selects events where the total number of PEs within 500 ns exceeds 270 PEs, using the hit information within this timeframe for further analysis. However, the trigger strategy must be optimized. As described in Sec. III, event spatial information was extracted and used together with hit time information as input to the discrimination algorithms.

III. Discrimination Methods

The fundamental principle behind discriminating pp solar neutrinos from ^{14}C double pile-up events is to utilize their distinct temporal and spatial characteristics (see Sec. II). Similar approaches have been applied to distinguish single-site and multi-site energy depositions in large-scale liquid scintillation detectors [46]. During measurement, the cluster structure is smeared by PMT dark noise and TTS, making identification more challenging and requiring more efficient approaches. This study performed multivariate analysis using the Toolkit for Multivariate Data Analysis (TMVA) [47,48], selecting the boosted decision trees with gradient boosting (BDTG) algorithm. Additionally, deep learning based on the VGG network was applied. Below we present details of the discrimination methods.

A. TMVA Analysis

TMVA [47,48] is a powerful multivariate analysis tool successfully applied to signal/background classification in accelerator physics [49], cosmic ray component identification [50], and event reconstruction in LS neutrino experiments [55]. The toolkit hosts various multivariate classification algorithms; we used the BDTG algorithm. To extract input variables, the PMT hit pattern was projected onto one-dimensional (1-D) distributions for hit time, , and ϕ in spherical coordinates. Projection results for Fig. 3(b) are shown in Fig. 5 [Figure 5: see original paper], and for Fig. 4(b) in Fig. 6 [Figure 6: see original paper]. The pp solar neutrino, being a single point-like event, shows only one cluster, whereas the ^{14}C double pile-up event shows two clusters. These 1-D distributions were used in multivariate analysis.

Input variables for TMVA algorithms should be sensitive to discrimination and capture characteristics of pp solar neutrinos and ^{14}C double-pile-up events. Our analysis found that hit time information dominated discrimination performance, so more variables were extracted from the 1-D hit time distribution. Fifteen variables were used in the TMVA analysis, denoted as V_i^{α}, where $i = 1, 2, 3$, etc., and $\alpha =$ hittime, θ, or ϕ indicates the source distribution. Details are provided in Table 3 . Fig. 7 [Figure 7: see original paper] shows normalized distributions of these input variables, with shape differences distinguishing the two event types. Correlations among input variables were checked for both pp solar neutrinos and ^{14}C double pile-up events. As shown in Fig. 8 [Figure 8: see original paper], after dropping variables with strong correlations in a previous study, the remaining correlations are acceptable (<90%). A few variables approach 90% correlation but were retained because they exhibit different correlations for signal and background, following a strategy similar to [56].

MC samples of pp solar neutrinos and ^{14}C double pile-up events were divided equally, with one half for TMVA training and the other for validation, yielding 50,000 events each for training and testing. To improve performance, key BDTG parameters were tuned; settings are shown in Table 4 . Other parameters used default values.

B. Deep Learning

Deep learning is widely used in high-energy and nuclear physics with many successful applications [51–55,57,58] including energy reconstruction, track reconstruction, particle identification, and signal processing. This study applied the VGG convolutional neural network for feature recognition of one-dimensional sequences. Extracted PMT hit patterns were projected onto 1-D feature series for hit time, , and ϕ, producing patterns similar to Figs. 5 and 6. Features were extracted using a 1-D convolution kernel for the three series, with pooling layers for information compression and fully connected layers for particle classification. The model structure was based on VGG-16, including 13 convolution and pooling modules, three fully connected layers, batch normalization, and dropout processing.

In addition to 1-D projection, we attempted 2-D projection methods (Mercator, sinusoidal, and PMT arrangement-based [55,59]) as deep learning network input. However, performance did not improve and in fact slightly worsened. Given the small number of hits in the energy range of interest, we found cluster features were much more pronounced in 1-D projection but very discrete in 2-D projection. Consequently, 1-D projection was used as input to the VGG network. We trained the VGG network using adaptive momentum with batch size 256, momentum 0.9, and initial learning rate 0.01, reducing the learning rate by a factor of 10 every 10 epochs. Model accuracy was evaluated using cross-entropy loss. For VGG network discrimination, 80% of pp neutrino and ^{14}C double-pile-up events were used for training, with the remaining 20% for validation.

IV. Discrimination Performance and Discussion

A. Discrimination Performance of the BDTG Model

Fig. 9 [Figure 9: see original paper] shows the BDTG model training results. The network was not overtrained, as testing data responses were consistent with training data (Fig. 9(a)). Signal and background separated into two parts after training, though some overlap remained, indicating similar event features. Detailed investigation revealed that one main reason for identification failure was stacking of two ^{14}C atoms very close in both time and space. To optimize significance $N_s/\sqrt{N_s+N_b}$, where N_s and N_b are signal and background numbers after identification, we scanned the BDTG response cut value and obtained corresponding efficiencies. Assuming a ^{14}C concentration of 5×10^{-18} g/g (Fig. 9(b)), significance calculations using one-day statistics in the analysis region (true energy: 160–250 keV) yielded 1653 signal events and 712,440 background events (considering only ^{14}C double pile-up) before identification. For the BDTG model, significance reached a maximum value of 10.33 after applying a cut at 0.915, with signal efficiency 51.1% and background rejection efficiency 99.18%. As discussed in Sec. I, the signal-to-background ratio of pp neutrinos to ^{14}C double-pile-up events is low in large-scale LS detectors, requiring strict cuts to reject most background. In this context, 51.1% signal efficiency is acceptable and still corresponds to many more effective pp neutrino signals per day than most existing experiments.

Fig. 9(c) evaluates significance for different ^{14}C concentration assumptions, while Fig. 9(d) shows the signal-to-background ratio after identification using the BDTG model based on one-day statistics for different concentrations. The BDTG model exhibits excellent performance and can effectively handle most ^{14}C double pile-up events. Other TMVA algorithms were also investigated, including likelihood and several BDT models (BDT and BDTD), many showing similar performance (Fig. 10 [Figure 10: see original paper]), demonstrating robustness and stability.

B. Discrimination Performance of the VGG Network

Fig. 11 [Figure 11: see original paper] shows VGG network training results. The network was not overtrained, as testing data responses matched training data (Fig. 11(a)). To optimize significance, we scanned VGG output cut values and obtained corresponding efficiencies. Assuming a ^{14}C concentration of 5×10^{-18} g/g (Fig. 11(b)), significance was calculated using one-day statistics in the analysis region based on Table 1. For the VGG network, significance reached a maximum of 15.55 after applying a cut at 0.975, with signal efficiency 42.7% and background rejection efficiency 99.81%.

Fig. 11(c) evaluates significance for different ^{14}C concentration assumptions, while Fig. 11(d) shows the signal-to-background ratio after VGG network identification based on one-day statistics for different concentrations. The VGG network demonstrates excellent performance, achieving higher significance and better signal-to-background ratio improvement compared to the BDTG model. Fig. 12 [Figure 12: see original paper] compares discrimination performance across different MC samples. Performance worsened when including PMT dark noise, while TTS had only minor influence. The VGG network discrimination performance remained stable when rejecting 99.8% of ^{14}C double pile-up events.

V. Summary

Large-scale LS detectors offer benefits of large target mass and high energy resolution, providing good potential for pp solar neutrino detection. However, they face a serious challenge from ^{14}C pile-up background. This study investigated discrimination between pp solar neutrinos and ^{14}C double-pile-up events in large-scale LS detectors using multivariate analysis and deep learning. In our simulation, we built a spherical LS detector using Geant4 with comprehensive optical processes. Comparing PMT hit pattern response features revealed clear differences in temporal and spatial distributions, as one is a single point-like event while the other is an accidental coincidence of multiple events.

Using the BDTG model for pp neutrino and ^{14}C double-pile-up discrimination at a ^{14}C concentration of 5×10^{-18} g/g, a signal significance of 10.3 can be achieved using only one day of statistics. Signal efficiency is 51.1% when rejecting 99.18% of ^{14}C double-pile-up events. With the VGG network model, signal significance can reach 15.6 using one day of statistics, with signal efficiency 42.7% when rejecting 99.81% of ^{14}C double-pile-up events. This analysis provides a reliable reference for similar experiments in low-threshold physics detection and ^{14}C pile-up background reduction.

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Note: Figure translations are in progress. See original paper for figures.