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Discrimination between neutrino events and backgrounds using pulse shape information in reactor neutrino experiments

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ABSTRACT

The application of Bayesian neural networks (BNN) to discriminate neutrino events from backgrounds in reactor neutrino experiments has been described in Xu et al. (2008) [1] and Xu et al. (2009) [2]. In the present paper, the pulse shape information for a fast signal of a neutrino event or a background event is used as a part of inputs to BNN to discriminate neutrino events from backgrounds. The numbers of photoelectrons received by PMTs and the delay time for a delayed signal are used as the other part of inputs to BNN (Xu et al., 2009) [2]. As a result, compared to Xu et al. (2009) [2], the identification efficiency of fast neutron background events is significantly improved using the BNN in the present paper. The other identification efficiencies are consistent with those in Xu et al. (2009) [2].

1. Introduction

The main goals of reactor neutrino experiments are to detect $\overline{\nu_e} \rightarrow \overline{\nu_x}$ oscillation and precisely measure the mixing angle of neutrino oscillation θ_{13}. The experiment is designed to detect reactor $\overline{\nu_e}$'s via the inverse β-decay reaction

$$\overline{\nu_e} + p \rightarrow e^+ + n.$$

The signature is a delayed coincidence between e^+ and the neutron capture signals. In Ref. [2], the numbers of photoelectrons received by PMTs and the delay time of a delayed signal are used as inputs to Bayesian neural networks (BNN) [3,4] to discriminate neutrino events from backgrounds and the background to signal ratios are significantly reduced, except the fast neutron background to signal ratio. In order to improve the identification efficiency for fast neutron background events, the pulse shape information for a fast signal of a neutrino event or a background event will be used to discriminate neutrino events from backgrounds. The pulse shape for the fast signal of a fast neutron event is different from that of a neutrino event, because the prompt signal of a fast neutron event is from recoiling proton, but the fast signal of a neutrino event is from recoiling electron induced by γ signals. Fig. 1 shows the two kinds of pulses induced by the fast signals of a neutrino event and of a fast neutron event. The information extracted from the pulse shape is used as a part of inputs to BNN, then discrimination between a neutrino event and a fast neutron events will be improved.

In the paper, the pulse shape information and the numbers of photoelectrons received by PMTs will be used as inputs to the BNN which will be applied to discriminate between neutrino events and background events in the signal region (see Ref. [1]) in the toy detector which is used to simulate central detectors in the reactor neutrino experiments with CERN GEANT4 package [5].

2. Toy detector and Monte-Carlo simulation

Three hundred and sixty-six PMTs are arranged in the toy detector which is the same as Ref. [6]. Eight rings of 30 PMTs are on the lateral surface of the oil region, and five rings of 24, 18, 12, 6, 3 PMTs are on the top and bottom caps.

Monte Carlo events which are used to train BNN and test BNN are generated by the same methods as Ref. [2]. They are uniformly generated throughout the Gd–LS region. A neutrino event is generated according to the anti-neutrino interaction in detectors of the reactor neutrino experiments [7]. A uncorrelated background event is generated in such a way that a γ event generated on the base of the energy distribution of the natural radioactivity in the proposal of the Daya Bay experiment [8] is regarded as the fast signal, a neutron event of the single signal is regarded as the delayed signal, its delay time is uniformly generated from 2 to 100 μs. The energy of a fast neutron event is uniformly generated from 0 to 50 MeV, therein an event of two signals is regarded as a fast neutron background event. Since the behaviors of ^{8}He/^{9}Li decay events in detectors could not be simulated by the Geant4 package, a ^{8}He/^{9}Li event is generated in such a way that the neutron signal from a fast neutron event is regarded as its delay signal, an electron event generated at the same position as the fast

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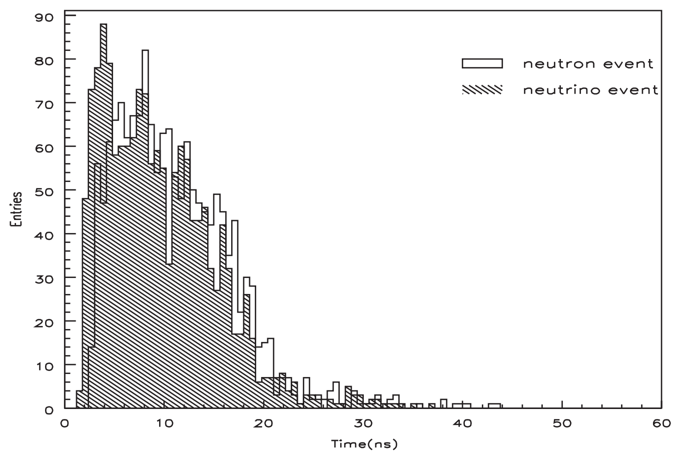

Fig. 1. The two kinds of the pulses induced by the fast signals of a neutrino event and a fast neutron event.

neutron event on the base of the energy distribution of $^{8}He/^{9}Li$ events in the proposal of the Daya Bay experiment [8] is regarded as its fast signal in the paper.

Energies and positions of neutrino events and backgrounds are reconstructed by the method in Ref. [6]. The signal region is determined by using the reconstructed energies and positions, as well as the neutron delay time (described in Ref. [1]).

3. Discrimination between neutrino events and background with BNN

The idea of BNN is to regard the process of training a neural network as a Bayesian inference. Bayes' theorem is used to assign a posterior probability density to each point, $\overline{\theta}$, in the parameter space of neural networks. Each point $\overline{\theta}$ denotes a neural network. In the methods of BNN, one performs a weighted average over all points in the parameter space of the neural network, that is, all neural networks. The method is described in detail in Refs. [3,4].

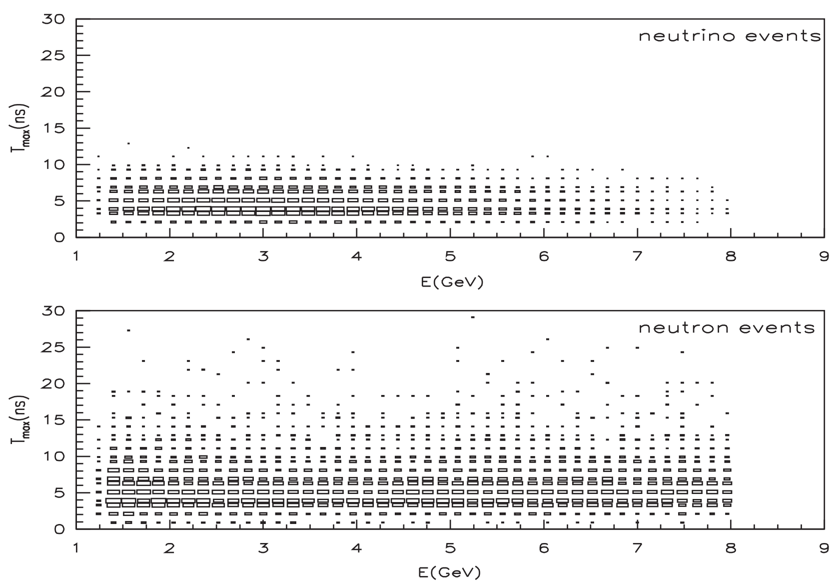

Fig. 2. The top figure is the distribution of neutrino events; the bottom one is the distribution of fast neutron events. *x* coordinate is energy, and *y* coordinate is the pulse time of arriving at the maximum height. The area of boxes in the figure is proportional to bin content.

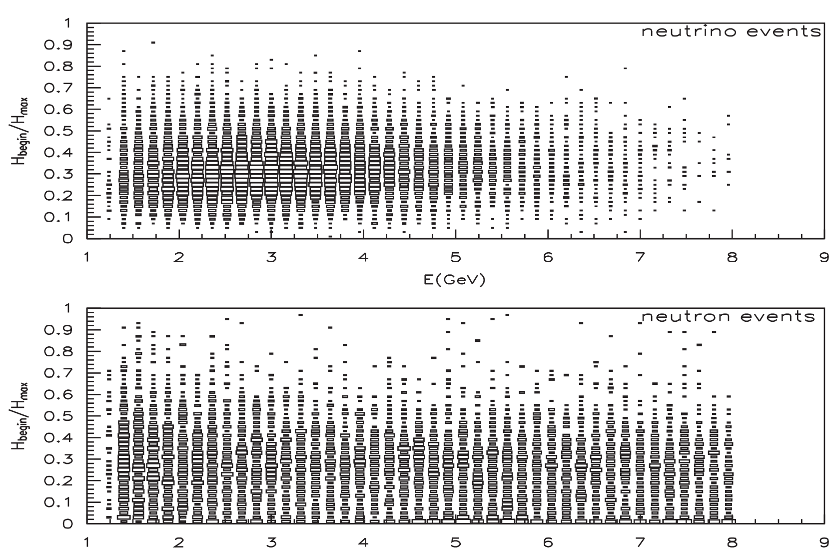

Fig. 3. The top figure is the distribution of neutrino events; the bottom one is the distribution of fast neutron events. *x* coordinate is energy, and *y* coordinate is the ratio between the beginning height and the maximum height. The area of boxes in the figure is proportional to bin content.

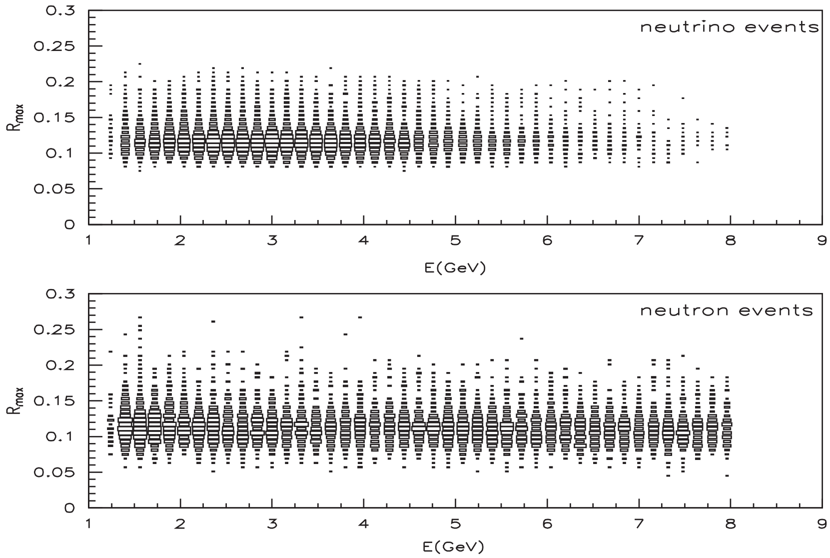

Fig. 4. The top figure is the distribution of neutrino events; the bottom one is the distribution of fast neutron events. *x* coordinate is energy, and *y* coordinate is the ratio between the maximum height and the pulse integral area. The area of boxes in the figure is proportional to bin content.

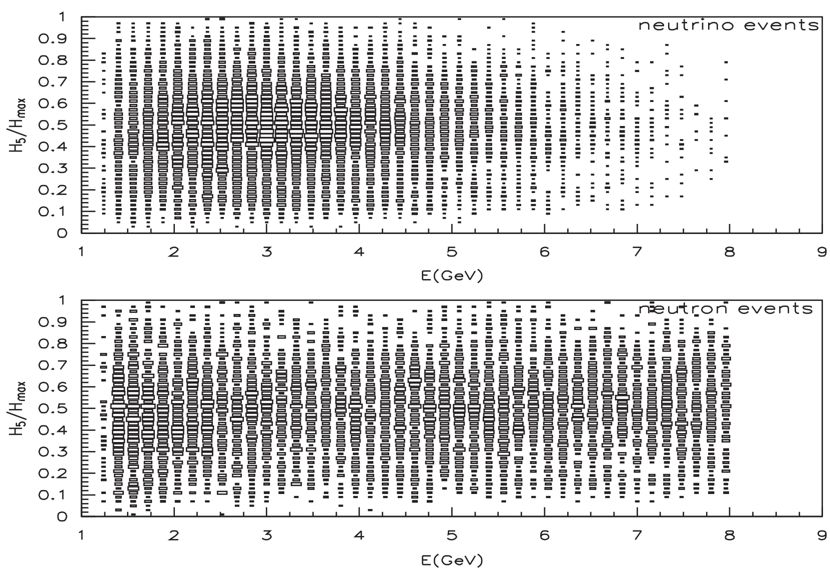

Fig. 5. The top figure is the distribution of neutrino events; the bottom one is the distribution of fast neutron events. *x* coordinate is energy, and *y* coordinate is the ratio between the height at 5 ns after arriving at the maximum height and the maximum height. The area of boxes in the figure is proportional to bin content.

3.1. *Inputs extracted from pulse shape information*

The discrimination between neutrino events and most background events is significantly improved using the BNN in Ref. [2] in comparison with the method in Ref. [1], but the one between neutrino events and fast neutron background events is worse. The pulse shape information for fast signals can be used to discriminate neutrino events from background events. In the paper, 10 variables are extracted from pulse shape information:

- T_{max}, the pulse time of arriving at the maximum height;
- H_{begin}/H_{max}, the ratio between the beginning height and the maximum height;
- R_{max}, the ratio between the maximum height and the pulse integral area;
- H_5/H_{max}, the ratio between the height at 5 ns (nanosecond) after arriving at the maximum height and the maximum height;
- H_{10}/H_{max}, the ratio between the height at 10 ns after arriving at the maximum height and the maximum height;
- H_{15}/H_{max}, the ratio between the height at 15 ns after arriving at the maximum height and the maximum height;
- T_0, the pulse time when the height becomes 0 after arriving at the maximum height;
- T_{max}/T_0;
- H_{10}/H_5, the ratio between the height at 10 ns after arriving at the maximum height and the height at 5 ns after arriving at the maximum height;
- H_{15}/H_5, the ratio between the height at 15 ns after arriving at the maximum height and the height at 5 ns after arriving at the maximum height.

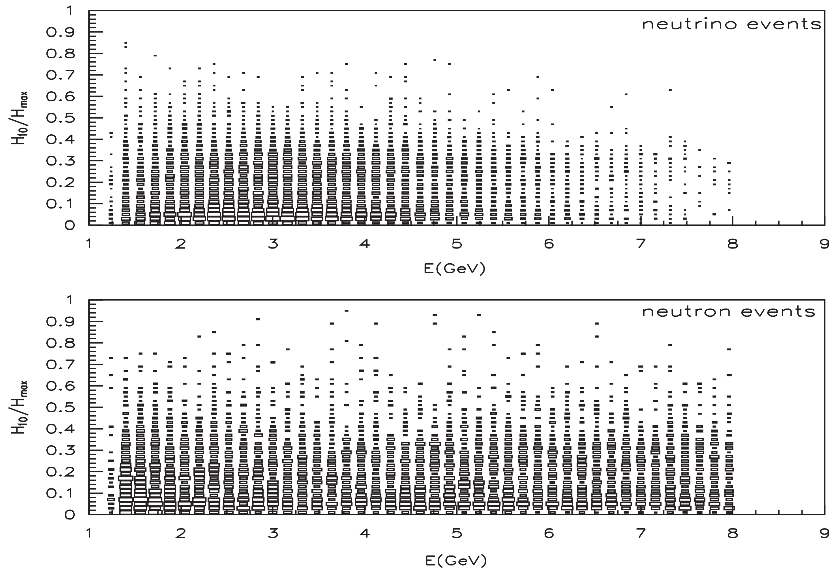

Fig. 6. The top figure is the distribution of neutrino events; the bottom one is the distribution of fast neutron events. *x* coordinate is energy, and *y* coordinate is the ratio between the height at 10 ns after arriving at the maximum height and the maximum height. The area of boxes in the figure is proportional to bin content.

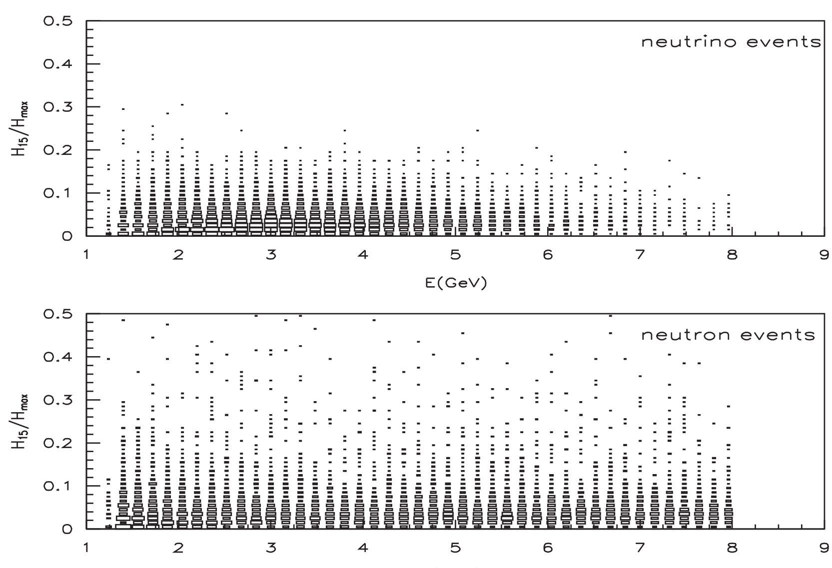

Fig. 7. The top figure is the distribution of neutrino events; the bottom one is the distribution of fast neutron events. *x* coordinate is energy, and *y* coordinate is the ratio between the height at 15 ns after arriving at the maximum height and the maximum height. The area of boxes in the figure is proportional to bin content.

Figs. 2–11 show the 10 variables distributions of neutrino events are different from those of fast neutron events.

3.2. Event identification with BNN

The 10 variables and the other 52 variables (see Ref. [2]) are used as inputs to BNN. Then all the networks have a input layer of 62 inputs, the single hidden layer of 15 nodes and a output layer of a single output which is just the probability that an event belongs to the neutrino event. Discriminating neutrino events from backgrounds is actually a binary response problem. Neutrino events are labeled by $t = 1$, and background events are labeled by $t = 0$. So the output of BNN has to be a number between 0 and 1. If the output is less than 0.5, the event is regarded as a background event, and If the output is larger than 0.5, it is regarded as a neutrino event.

A Markov chain of neural networks is generated using the Bayesian neural networks package of Radford Neal,[1] with a training sample consisting of neutrino events and background events. The Markov chain in the parameters space of neural networks has 1000 points. They are saved to lessen the correlation after 20 MCMC (Markov chain Monte Carlo) steps here. The initial part of the Markov chain must be discarded because the correlation between the initial point of the chain and the point of the part is very high. The initial 300 points are discarded here. It

[1] R. M. Neal, *Software for Flexible Bayesian Modeling and Markov Chain Sampling*, http://www.cs.utoronto.ca/ ~ radford/fbm.software.html

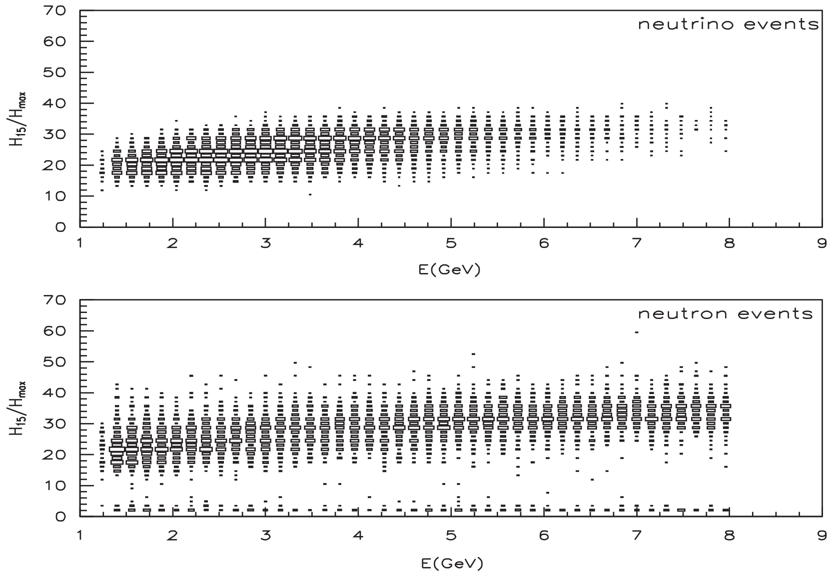

Fig. 8. The top figure is the distribution of neutrino events; the bottom one is the distribution of fast neutron events. *x* coordinate is energy, and *y* coordinate is the pulse time when the height becomes 0 after arriving at the maximum height. The area of boxes in the figure is proportional to bin content.

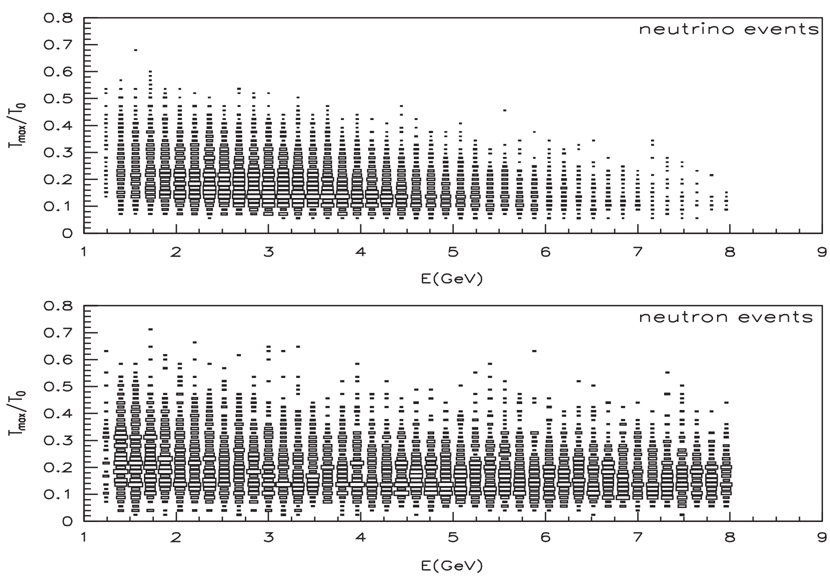

Fig. 9. The top figure is the distribution of neutrino events; the bottom one is the distribution of fast neutron events. *x* coordinate is energy, and *y* coordinate is the rate between the time when a pulse reaches its maximum height and the time when the height reaches 0 after the maximum height. The area of boxes in the figure is proportional to bin content.

takes about 140 h to run 1000 points on a computer with two 3.4 GHz Intel Pentium D processors (only one of which is used).

4. Results and discussion

Neutrino identification efficiencies are defined by the ratios between the number of events in neutrino test sample regarded as neutrinos and the number of neutrino test sample. Background identification efficiencies are defined by the ratios between the numbers of the events in background test samples regarded as background events and the numbers of background test samples. The identification efficiencies are measured with the test sample which is different from the training sample. Other 3000 events each of the neutrino and the three backgrounds are used to test the identification capability of the trained BNN. In the paper, BNN are trained by the different training samples, which consist of neutrinos and three backgrounds at different rates, since the different identification efficiencies are obtained using those BNN.

As Table 1 shows, the discriminations between neutrino events and backgrounds of uncorrelated events and $^{8}He/^{9}Li$ events are consistent with Ref. [2]. However, fast neutrons identification efficiencies are significantly improved. Compared to Ref. [2], they increase by about 43–60%. So the fast neutron background to signal ratio is correspondingly reduced. If the fast neutron identification efficiencies of the first column in Table 1 are use for the comparison, the fast neutron background to signal ratio in Ref. [2] is $0.751 * (F/N)$ and the one in the paper is $0.563 * (F/N)$. F/N is the fast neutron background to neutrino events ratio in the signal region [2] using the method based on the cuts. The fast neutron background to neutrino events ratio is significantly improved. So the BNN method in the paper is better applied to discriminate between neutrino events and background events than the one in Ref. [2].

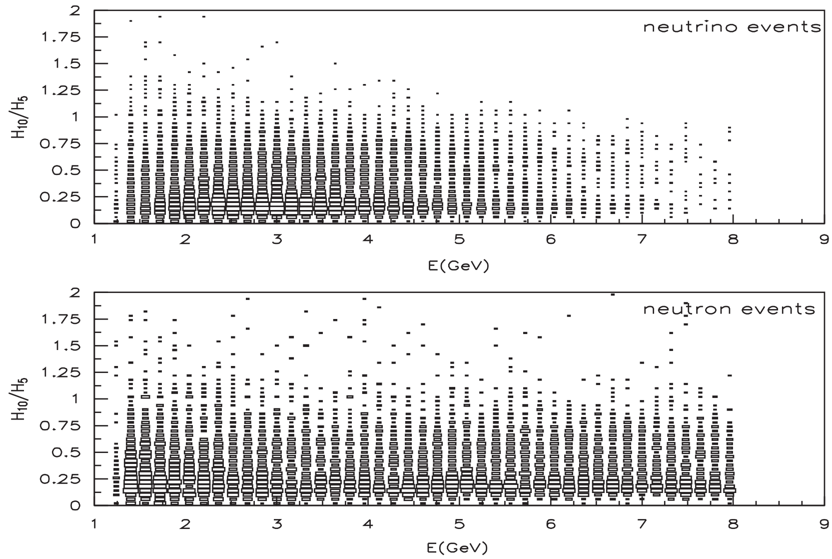

Fig. 10. The top figure is the distribution of neutrino events; the bottom one is the distribution of fast neutron events. *x* coordinate is energy, and *y* coordinate is the ratio between the height at 10 ns after arriving at the maximum height and the height at 5 ns after arriving at the maximum height. The area of boxes in the figure is proportional to bin content.

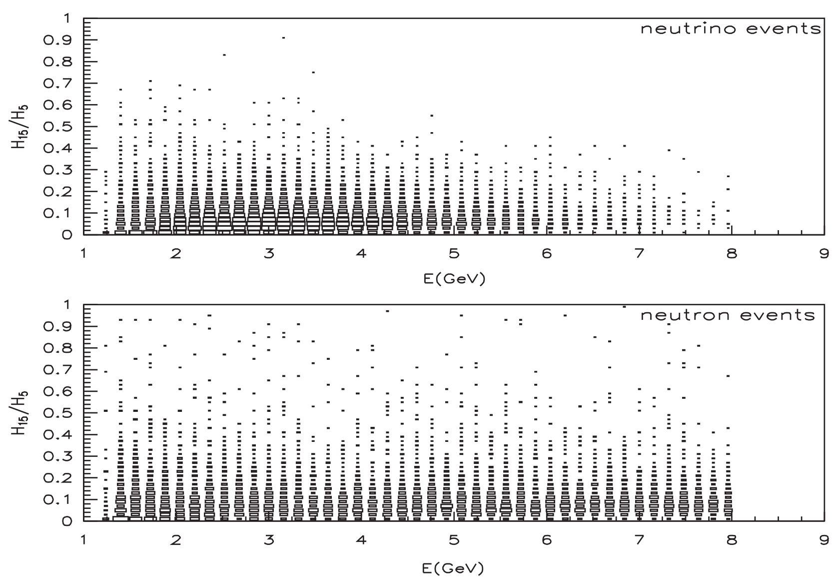

Fig. 11. The top figure is the distribution of neutrino events; the bottom one is the distribution of fast neutron events. *x* coordinate is energy, and *y* coordinate is the ratio between the height at 15 ns after arriving at the maximum height and the height at 5 ns after arriving at the maximum height. The area of boxes in the figure is proportional to bin content.

Table 1
The different identification efficiencies are obtained with the BNNs trained by the different training samples, which consist of the neutrino and three backgrounds at different rates.

Neutrino rate (%)	50.0	50.0	54.5	57.1
Uncorrelated background rate (%)	16.7	12.5	9.1	9.5
Fast neutron rate (%)	16.7	25.0	27.3	23.8
^{8}He/^{9}Li rate (%)	16.7	12.5	9.1	9.5
Neutrino eff. (%)	94.5 ± 0.42	92.4 ± 0.48	93.0 ± 0.47	94.4 ± 0.42
Uncorrelated background eff. (%)	98.0 ± 0.26	97.6 ± 0.28	95.6 ± 0.37	95.9 ± 0.36
Fast neutrons eff. (%)	46.8 ± 0.91	51.2 ± 0.91	49.9 ± 0.91	47.6 ± 0.91
^{8}He/^{9}Li eff. (%)	90.4 ± 0.54	89.4 ± 0.56	86.6 ± 0.62	86.8 ± 0.62

The term after $\pm$ is the statistical error of the identification efficiencies. The numbers of the train samples are 24 000, respectively. The 3000 events each of the uncorrelated background, fast neutron and ^{8}He/^{9}Li are regarded as the test sample.

Acknowledgments

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