The Neutron-Gamma Pulse Shape Discrimination of CLLB Detector

Ruiqiang Song1,2, Shuo Peng2, Yufeng Tong3, Qi Wu2, Sen Qian2*, Zhigang Wang2, Jifeng Han1

1 Key Laboratory of Radiation Physics and Technology of the Ministry of Education, 610064 Sichuan University, China
2 Institute of High Energy Physics, 100049 Chinese Academy of Sciences, China
3 College of Materials and Chemistry, 3100118 China Jiliang University, China

Abstract. Cs2LiLaBr6: Ce (CLLB) scintillator with the size of Φ 21 mm × 25 mm coupled with PMT was used to detect neutron and gamma rays. The pulse shape discrimination (PSD) of neutrons and gamma rays by charge comparison method, the neutrons and gamma rays from AmBe source and fast neutron beam can be separated with figure-of-merit (FOM) values of 0.9 and 1.3, respectively. However, some neutron and gamma rays are difficult to distinguish, so new algorithms need to be investigated to improve the PSD performance of neutron and gamma. Artificial neural networks (ANN) have a very good image recognition capability, thus the ANN model was constructed to discriminate the waveforms of neutron and gamma rays. After ANN model training, the neutron and gamma signals of the CLLB detector were recognized with an accuracy of 98%, and the FOM value of the ANN method was calculated to be 19.4. This result is much higher than the charge comparison method, indicating better discrimination between neutrons and gamma rays with the ANN method.

1. Introduction

Neutron detection has a wide range of applications as homeland security [1], neutron imaging systems [2], and environmental monitoring [3]. The lithium-containing scintillator Cs2LiLaBr6: Ce (CLLB) belongs to the elpasolite family, which exhibits good thermal neutron detection efficiency and excellent energy resolution (<5% for 662keV gamma rays), and high light yield (180,000) [4]. With the rapid development of Analog-to-Digital (ADC), nuclear radiation pulse signals can be digitized to obtain more information. Digital pulse shape discrimination (PSD) has received much attention for neutron and gamma signal discrimination. The charge integration method is the most commonly used PSD method. Since neutrons and gamma rays in CLLB have different emission mechanisms, the gamma component has a slower decay compared to neutrons, leading to differences in pulse waveforms. Therefore neutron and gamma signals can be discriminated by the PSD method. Although the conventional charge comparison method has good PSD performance for

* Corresponding author: qians@ihep.ac.cn
waveforms with high variability in decay components, it is less effective in discriminating waveforms with low variability. In addition, the discrimination effect of the charge comparison method tends to depend on the selection of the window parameters, which needs to be traversed to find the optimal values and this process takes a lot of time and effort. In recent years, machine learning is widely used in image recognition, Artificial neural networks (ANN) are one of the most commonly used models for machine learning[5], which can construct complex models to deal with nonlinear problems through multi-layer nonlinear mapping, and can learn generalized patterns and features from data with strong generalization ability. It can handle noise, missing data, and changing inputs with some robustness. Therefore, an ANN method for the discrimination of neutron and gamma waveforms is attempted in this work.

2. Materials and methods

In our experiment, we used the CLLB scintillator (Φ 21mm × 25 mm length) by China Jiliang University with 17% ⁶Li abundance. The CLLB scintillator is capable of detecting neutrons based on ⁶Li(n, α)³H reaction and has a high thermal neutron capture cross-section (940 barn). The Hamamatsu R580 PMT was coupled with the CLLB for gamma and neutron detection. The high-speed digitizer ADQ12DC from Teledyne SP Devices company with a sampling rate of 1 GHz is used for data acquisition. The neutron and gamma signals are acquired with a detection window of 10240 ns. To investigate the discrimination capability of the CLLB scintillator for neutron and gamma rays, the experiment used a AmBe neutron source with an activity of about 50 kBq is moderated by paraffin wax with 5cm thick to obtain thermal neutrons. To further investigate the response of CLLB to fast neutron, the 2.0 MeV deuteron beam was injected on a D/Ti target to generate a 5.2 MeV neutron beam by D(d, n)³He reaction from the 3MV tandem accelerator in Sichuan University [6].

In this work, the CLLB detector was measured under the AmBe source and 5.2 MeV neutron beam, respectively. We used the traditional charge comparison method to discriminate the neutron and gamma pulses of the CLLB detector. After discrimination, the signals are divided into two groups: a neutron signals set and a gamma signals set. The gamma and neutron signals are labeled with 0, 1 respectively, and then the signals are randomly divided into a training set and a test set. The training set is used to train the ANN, while the test set verifies the discrimination performance of the ANN.

3. Neutron-gamma discrimination

3.1 Neutron-gamma discrimination of charge comparison method

The charge comparison method is a traditional method to discriminate between the neutron and gamma signals. The PSD of the charge comparison method is to reflect the difference in the shape of the waveform through the difference of a feature quantity PSD=f(x) that describes the shape. The greater the variability of PSD values between neutron and gamma signals, the better the discrimination performance, the PSD value can be defined as:

\[ R_{psd} = \frac{\int_{t_0}^{t_0+t_1} f(t)dt}{\int_{t_0}^{t_0+t_2} f(t)dt} \]

where \( t_0 \) is the start time of the pulse, \( t_1 \) is the length of the short integral interval and \( t_2 \) is the length of the long integral interval. The integration window from \( t_0 \) to \( t_1 \) is called the short
window, and the integration window from $t_0$ to $t_2$ is called the long window. Under this condition, choosing the suitable combination of integration windows can obtain the optimal discrimination performance. The figure-of-merit (FOM) was introduced to evaluate PSD performance, and the definition of FOM is the ratio of the difference between the center values of the two cluster distributions to the sum of the Full Width Half maximum (FWHM), as shown in Eq. (2):

$$\text{FOM} = \frac{\mu_n - \mu_\gamma}{\text{FWHM}_n + \text{FWHM}_\gamma}$$

(2)

where FWHM$_n$, FWHM$_\gamma$ represents the FWHM of gamma peak and neutron peak; $\mu_n$, $\mu_\gamma$ represents the peak position of gamma and neutron peaks.

By optimizing the integration window, the short and long windows under the AmBe neutron source are set to 360 ns and 2400 ns, respectively. The neutrons and gamma rays discrimination was performed by the charge comparison, the PSD scatter plot as shown in Fig. 1(a). The distribution of PSD values for neutrons and gamma rays is divided into two parts, with the top blue scatter for neutrons and the bottom red scatter for gamma. The PSD values of neutrons are higher than those of gamma rays, which is due to the fact that the decay time of gamma rays is more slowly in the CLLB scintillator. In Fig.1(a), one can see that pulses of neutrons and gamma rays can be discriminated, but the discriminating effect is not good, and some neutron and gamma instances cannot be discriminated, such as neutron and gamma-ray signals with PSD values near 0.33. The mean gamma/electron equivalent energy of thermal neutrons is $\sim$3.2 MeVee, which is due to the $^6\text{Li}(n,\alpha)^3\text{H}$ reaction with Q value of 4.78 MeV as well as the quenching effect within the scintillator [7]. Fig. 1(b) shows the 1D PSD histogram on the thermal neutron peak region ($3.0 < E < 3.4$ MeVee), The FOM value of 0.9, and it’s neutron and gamma discrimination performance is worse than that of the CLYC detector [8,9]. In addition, we measured the CLLB detector under 5.2 MeV fast neutron beam for investigating the fast neutron response of the CLLB detector. Neutrons and gamma rays are discriminated by the charge comparison method with optimized short and long windows of 180 ns, 1,000 ns. The PSD scatter plot and 1D PSD histogram as shown in Fig. 2. One can be seen that scattered neutrons and gamma are clearly distinguished (shown in black box) as shown in Fig. 2 (a). The scattered neutrons here come from the scattering of fast neutrons with their surroundings. The FOM value is 1.3 for scattered neutrons and gamma rays is better than the FOM values for thermal neutrons and gamma rays under the AmBe source. The fast neutron response of the CLLB detector under a fast neutron beam is not significant and the neutron region is dominated by scattered neutrons.

![Fig. 1. The PSD scatter plot (a) and 1D PSD histogram (b) for CLLB under AmBe neutron source.](image-url)
Fig. 2. The PSD scatter plot (a) and 1D PSD histogram (b) for CLLB under fast neutron beam.

About 400 neutrons and gamma rays pulses were averaged from the AmBe source and fast neutron beam, as shown in Fig. 3. The rise time of the averaged waveform is defined as the time interval located between 10 % ~ 90 % of the peak value of the amplitude on the rising edge, and the fall time is defined as the time interval between 10 % ~ 90 % of the peak value on the falling edge. The rise and fall times of the average waveforms are listed in Table 1. Comparing the average waveforms of neutrons and gamma rays under the AmBe source and fast neutron beam, it can be seen that the rise time of the average waveforms of neutrons and gamma rays is basically around 22 ns, with little difference. The fall times for neutrons and gamma rays under the AmBe source are slightly larger than those under the neutron beam. In general, gamma rays have slower decay times than neutrons.

Fig. 3. The average pulses of neutron and gamma from the AmBe source and fast neutron beam.

Table 1. The rise time and fall time of average waveforms from the AmBe source and fast neutron beam

<table>
<thead>
<tr>
<th>Type</th>
<th>γ-ray rise time [ns]</th>
<th>Neutron rise time [ns]</th>
<th>γ-ray fall time [ns]</th>
<th>Neutron fall time [ns]</th>
</tr>
</thead>
<tbody>
<tr>
<td>AmBe</td>
<td>26</td>
<td>22</td>
<td>727</td>
<td>614</td>
</tr>
<tr>
<td>Neutron beam</td>
<td>23</td>
<td>21</td>
<td>689</td>
<td>563</td>
</tr>
</tbody>
</table>

3.2 Neutron-gamma discrimination of ANN method

The ANN is the core of deep learning, which is a computational model that simulates the neuronal structure of the human brain. It has powerful learning capabilities often used for classification and prediction, as well as decision-making on complex data. In this work, ANN networks were constructed using the Keras (version 2.6) and Tensorflow (version 2.10)
packages by Google [10]. The entire network structure consists of 3 hidden layers and an input layer of shape (1, 5000) and an output layer. The number of neurons in the hidden layer is 300, 100, and 100, respectively. The activation function "ReLU" is used in each hidden layer to improve the energy of the ANN to deal with nonlinearity avoiding gradient vanishing. The output layer has only one neuron and "Sigmoid" is used as an activation function for the classification of neutron and gamma signals. The input dataset for the ANN is derived from neutrons and gamma rays obtained by the charge comparison method from the AmBe source and fast neutron beam. The dataset consists of two parts, the training set, and the test set. The training set constitutes 80% of the total dataset while the test set is 20%. In addition, 20% of the training set is used as validation in ANN. To prevent overfitting, about 30% of the parameters were randomly discarded and L2 regularization was used. The optimizer was set to Adam with a learning rate of 0.001, and the "binary cross_entropy" as a loss function [11]. The schematic diagram of ANN model structure is shown in Fig. 4.

Fig. 4. Schematic diagram of ANN model structure

After inputting the neutron and gamma signals shown in Fig. 3 into the ANN, the pulses are normalized and the gamma rays and neutrons are marked as 0 and 1, respectively. The accuracy and loss curves during training are shown in Fig. 5 (a) and (b), respectively. It can be seen that the accuracy and loss values change smoothly and the model converges normally without overfitting. After 30 epochs, the accuracy curve stabilizes and the average accuracy of the training and validation sets is about 98%. After 100 epochs, the loss values of the training and validation sets are close to about 0.015. Using the model to predict the output of the test data, the accuracy is 98%, which shows that the ANN model is very effective in discriminating between neutrons and gamma rays.

Fig. 5. The ANN model's accuracy (a) and loss (b) curves in the train set and validation set.
Fig. 6 shows the distribution of the 2-D PSD values obtained by the ANN model and the projection of the PSD values on 1-D. By fitting Fig. 6 (b) to Gaussian, we obtained the half-height widths of PSD values as well as the peak positions for neutrons and gamma rays. According to Eq. (2), the FOM value of the ANN is calculated to be 19.4.

By comparing with the charge comparison method, the ANN method can perform the discrimination of neutrons and gamma rays efficiently. In addition, the ANN method has a good generalization ability, which enables efficient discrimination of neutron and gamma signals from AmBe sources as well as fast neutron beam.

4. Conclusions

In this study, the CLLB detector has demonstrated dual n/γ detection capability for both AmBe sources and fast neutron beam. The neutrons and gamma rays were discriminated by the charge comparison method, with a FOM value of 0.9 for the AmBe source worse than 1.3 for the fast neutron beam. After further analyzing the averaged waveforms of neutrons and gamma rays, it was found that the rise and fall times of the gamma-ray and neutron waveforms of the AmBe source differed less from those of the fast neutron beam. Therefore, the neutrons and gamma rays discriminated by the charge comparison method were utilized to create the dataset. An ANN model is used to discriminate neutrons and gamma rays from the AmBe source as well as fast neutron beam. It is found that the ANN can effectively extract the feature information of the pulse, and the "Sigmoid" activation function is added to the output layer to realize the classification of neutron and gamma signals. The neutrons and gamma rays were discriminated by the ANN model, obtaining an accuracy of about 98%, and loss value of about 0.015. In addition, the FOM value of neutrons and gamma rays of the CLLB detector can be improved to 19.4 by the ANN method. Compared with the traditional charge comparison method, the ANN method has a high accuracy and generalization ability, which provides a new method for distinguishing neutrons and gamma rays.

References