

Research on n/γ Discrimination Method Based on Deep Metric Learning

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Abstract

Precise discrimination of neutrons and gamma rays in complex radiation environments is a critical technology in the fields of nuclear material detection and nuclear security. Current mainstream end-to-end neural network classification models exhibit insufficient generalization capability when confronted with timing jitter in electronic waveform characteristics. Therefore, this paper proposes an n/γ discrimination method based on deep metric learning, which designs an improved convolutional neural network architecture based on LeNet-5. Combined with triplet loss function constraints, a discriminative feature space for neutron and gamma nuclear pulses is obtained, achieving efficient discrimination of neutrons and gamma rays. Training is performed using a hybrid dataset collected from a hardware-based nuclear pulse simulator and software-simulated data. Quantitative tests are conducted on both simulated data and measured pulse data with electronic waveform timing jitter, with comparisons made against the traditional charge comparison method and conventional CNN discrimination method. The results demonstrate that on simulated data, the Figure of Merit (FOM) of the proposed method is improved by 247.7% compared to the charge comparison method; on measured pulse data, the discrimination error rate is reduced by 70% compared to the conventional CNN discrimination method. This method can effectively address the problem of low generalization capability in conventional CNN discrimination methods, providing a novel approach for high-precision particle discrimination technology in radiation detection systems.

Full Text

Study on n/γ Discrimination Method Based on Deep Metric Learning

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Abstract

Precise discrimination of neutrons and gamma rays in complex radiation environments is a critical technology in nuclear material detection and nuclear safety. Current mainstream end-to-end neural network classification models suffer from insufficient generalization capability when confronted with jitter in electronic waveform temporal characteristics. To address this limitation, we propose an n/γ discrimination method based on deep metric learning. By designing an improved convolutional neural network architecture derived from LeNet-5 and incorporating triplet loss function constraints, we obtain a discriminative feature space for neutron and gamma nuclear pulses, enabling efficient n/γ discrimination. Training employs a hybrid dataset combining data collected from a hardware nuclear pulse simulator and software-simulated data. Quantitative testing was conducted on both simulation data and measured pulse data exhibiting electronic waveform temporal jitter, with comparative evaluation against traditional charge comparison methods and conventional CNN discrimination approaches. Results demonstrate that on simulation data, the Figure of Merit (FOM) of our proposed method improves by 247.7% compared to the charge comparison method. On measured pulse data, the discrimination error rate decreases by 70% compared to traditional CNN discrimination methods. This approach effectively resolves the low generalization capability issues inherent in conventional CNN discrimination methods, providing a novel framework for high-precision particle discrimination technology in radiation detection systems.

Keywords: n/γ discrimination; deep metric learning; triplet loss; charge comparison method; convolutional neural network

Neutron detection technology plays a vital role in numerous fields including nuclear radiation monitoring, nuclear safety, nuclear material detection, cosmic ray research, medical imaging, and particle physics experiments [1-3]. However, actual neutron radiation fields in practical applications are often accompanied by substantial gamma-ray backgrounds that interfere with signal quality and detection effectiveness of neutron detectors [4]. Therefore, accurate discrimination between neutrons and gamma rays in mixed radiation field environments represents a key scientific challenge for improving detection reliability and holds significant value for nuclear technology applications and radiation protection domains.

Existing n/γ discrimination techniques primarily rely on distinguishing pulse shape characteristics: when neutrons and gamma rays interact with scintillator materials, different energy deposition mechanisms produce pulse signals with distinct shapes [5]. Based on this principle, Pulse Shape Discrimination

(PSD) technology has evolved three traditional approaches: time-domain analysis, frequency-domain analysis, and machine learning methods. Time-domain methods include charge comparison [6], zero-crossing time [7], rise time [8], and pulse gradient analysis [9]. While straightforward to implement, these methods suffer from difficult parameter extraction and high noise sensitivity. Frequency-domain methods, such as frequency gradient analysis [10], can improve signal-to-noise ratios but their effectiveness heavily depends on the selection of frequency-domain feature parameters. Machine learning methods have improved certain performance aspects but still face challenges related to complex feature engineering.

Recent breakthroughs in artificial intelligence have provided new research directions for PSD technology [11]. Song et al. [12] utilized BP neural networks to optimize features from the charge comparison method, enhancing n/γ discrimination performance. Ronchi et al. [13] employed a one-dimensional CNN architecture to achieve superior discrimination performance compared to traditional methods. Huang et al. [14] proposed an n/γ discrimination method combining Gramian Angular Fields with CNNs, enabling fusion of temporal and frequency domain features. However, these deep learning-based PSD methods predominantly adopt direct classification approaches, failing to fully exploit the feature representation capabilities of deep learning. Furthermore, due to variations in front-end electronic parameters and environmental variables that cause pulse shape differences, these methods exhibit insufficient generalization capability when neural network discrimination models encounter jitter in electronic waveform temporal characteristics.

To address these issues, this paper proposes an n/γ discrimination method based on deep metric learning. This approach focuses on learning similarity metrics between samples, capable of capturing more refined feature representations [15-16]. First, we design and implement a hybrid data source construction method for training samples. Then, through training an improved CNN network with triplet loss functions, we capture more discriminative features distinguishing neutron and gamma ray pulses, learn deep feature representations of neutron and gamma pulse signals, and achieve n/γ discrimination classification using metric relationships between feature vectors. Finally, comprehensive experimental comparisons with traditional methods validate the effectiveness of our approach.

1.1 Data Acquisition Platform

The architecture and hardware composition of the data acquisition platform are illustrated in [Figure 1: see original paper]. The system comprises a pulse signal source, signal preprocessing circuit, data acquisition unit, and computing processing unit. A CAEN DT5800 nuclear pulse simulator provides n/γ mixed radiation fields, while Python software simulates n/γ mixed pulse signals based on characteristics of actual nuclear pulse signals. A high-voltage bias power supply provides gain power for the nuclear pulse simulator. A 14-bit ADC with

maximum sampling rate of 1.2 GHz digitizes neutron and gamma pulses at 500 MHz sampling rate, with acquired waveform data transmitted in real-time to the host computer for storage. A total of 20,000 valid pulse samples were collected.

1.2.1 Hardware-Collected Data

The nuclear pulse simulator generates pulse signals with typical n/γ characteristics. The simulator can adjust pulse rise time, fall time, and amplitude parameters to simulate different types of nuclear radiation events. The pulse generator output signals pass through signal conditioning circuits before digital sampling by an FPGA-controlled ADC.

To ensure data reliability, pulse parameters were set according to typical values from actual nuclear detection experiments: neutron pulse rise time of approximately 20-30 ns and fall time of 150-200 ns; gamma pulse rise time of 15-25 ns and fall time of 80-120 ns. Each pulse was sampled with 100 points to completely cover the rising and falling edges. This approach yielded 5,000 neutron pulse samples and 5,000 gamma pulse samples. [Figure 2: see original paper] shows a comparison of typical acquired n/γ pulse waveforms.

1.2.2 Software-Simulated Data

To further expand the dataset scale and increase data diversity, we developed a pulse simulation program in Python. The simulation model, based on pulse shape characteristics from actual nuclear physics experiments, employs a double exponential function to describe pulse waveforms, as shown in Equation (1):

$$V(t) = A(e^{-t/\tau_1} - e^{-t/\tau_2})$$

In Equation (1), A represents the amplitude coefficient, τ_1 denotes the fall time constant, τ_2 denotes the rise time constant, with $\tau_1 \gg \tau_2$. Since gamma pulse decay times are slightly shorter than neutron pulse decay times, the τ values for gamma pulses are set smaller than those for neutron pulses. To make the simulated data more realistic, we introduced the following random variations: pulse amplitude varies randomly within $\pm 15\%$ of nominal values; time constants vary within $\pm 10\%$ of nominal values; Gaussian white noise is added with SNR varying between 15-25 dB; baseline drift is randomly introduced with amplitude of $\pm 5\%$ of nominal values. Through software simulation, an additional 5,000 neutron pulse samples and 5,000 gamma pulse samples were generated. [Figure 3: see original paper] displays an example of the simulated pulse waveforms.

1.2.3 Data Preprocessing

Since analog-to-digital conversion by the ADC module may introduce high-frequency noise, and software-simulated pulses also contain added noise effects, pulse amplitude variations can impact processing results. To ensure data quality,

raw signals entering the host computer require preprocessing. The preprocessing pipeline consists of: baseline correction, smoothing filtering [17], and amplitude normalization. Baseline correction calculates the average of the first 10 pre-pulse points as the baseline and adjusts it to zero. Smoothing filtering employs moving average (arithmetic mean) filtering to eliminate high-frequency noise effects on discrimination results. Amplitude normalization uses linear function normalization to transform pulse signal amplitudes into the $[0,1]$ interval. After preprocessing, a complete dataset containing 19,927 pulse samples was obtained, with 80% allocated as training set (15,941 samples) and 20% as test set (3,986 samples) for subsequent calculations. [Figure 4: see original paper] compares pulse signals before and after preprocessing.

2.1 Principles of Deep Metric Learning

Deep metric learning employs deep neural networks to learn similarity metrics between samples. Its core concept maps raw data into a feature space where intra-class distances are minimized and inter-class distances are maximized. Compared with traditional classification methods, deep metric learning emphasizes feature representation and can capture more subtle inter-class differences, making it particularly suitable for fine-grained classification problems [15].

In n/γ discrimination tasks, neutron and gamma ray pulses exhibit similar overall shapes but possess subtle differences that become even more difficult to capture under noise interference. Deep metric learning enhances the ability to discriminate these minute differences by optimizing sample distribution in feature space. The deep metric learning discrimination workflow is shown in [Figure 5: see original paper].

2.2 Triplet Loss Function

The triplet loss function is a commonly used loss function in deep metric learning [15]. It adopts a triplet training strategy (anchor-positive-negative) that optimizes feature space distribution by minimizing distances between same-class samples (anchor and positive) while maximizing distances between different-class samples (anchor and negative) [15]. The mathematical expression of the triplet loss function is:

$$L = \max(D(f(x_a), f(x_p)) - D(f(x_a), f(x_n)) + \text{margin}, 0)$$

In Equation (2), x_a represents the anchor sample, x_p denotes the positive sample from the same class as the anchor, and x_n denotes the negative sample from a different class. $D(\cdot, \cdot)$ represents the distance function between feature vectors, and margin is a predefined boundary value controlling the distance difference between positive and negative pairs. [Figure 6: see original paper] illustrates the triplet loss function training schematic.

In this study, anchor samples are selected from neutron or gamma pulses, positive samples are pulses of the same class as the anchor, and negative samples are pulses from the different class. The cosine distance function is chosen as the distance metric. Through optimization with the triplet loss function, the network learns more discriminative feature representations, thereby improving n/γ discrimination accuracy.

2.3 Network Model Design

Based on extensive experimentation, we designed a CNN model suitable for pulse signal processing by building upon the classic LeNet-5 architecture. The overall network architecture is shown in [Figure 7: see original paper]. The ReLU function serves as the activation function during convolution, defined in Equation (3):

$$\text{ReLU}(x) = \max(0, x)$$

This activation function offers simple computation, avoids gradient vanishing problems, and accelerates convergence while improving model generalization capability. Compared with the traditional LeNet network, our improved architecture employs Dropout technology to mitigate overfitting. Dropout is applied to the outputs of fully connected layers 1 and 2 with a rate of 0.5, randomly disabling 50% of neurons during each training iteration to enhance network robustness. L2 normalization is added before feature vector output, constraining all feature vectors to the unit hypersphere to facilitate subsequent metric calculations. details the CNN model structure and layer parameter configurations.

2.4 Triplet Construction Strategy

Triplet selection significantly impacts model training effectiveness. Randomly selected triplets often already satisfy loss function constraints and contribute minimally to network parameter optimization. To improve training efficiency, this study employs semi-hard triplet mining [18] to focus optimization on the most valuable sample pairs. This strategy selects “moderately difficult” triplets that provide meaningful learning signals.

The implementation process is as follows: (1) Dynamic batch construction: Each mini-batch selects $P = 2$ class samples (neutrons and gamma rays) with K samples per class (e.g., $K = 10$), forming a batch of $PK = 20$ samples. (2) Feature extraction: Pulse waveforms are processed through the model to obtain feature representations. (3) Triplet construction: For each anchor sample (e.g., a neutron pulse), a same-class sample serves as the positive sample (another neutron pulse), while negative samples (gamma pulses) are selected from those satisfying the semi-hard condition based on distance to the anchor. Semi-hard triplet mining selects negative samples following Equation (4):

$$D(f(x_a), f(x_n)) > D(f(x_a), f(x_p)) \quad \text{and} \quad D(f(x_a), f(x_n)) < D(f(x_a), f(x_p)) + \alpha$$

In Equation (4), $f(x_a)$ represents the anchor sample feature, $f(x_p)$ the positive sample feature, $f(x_n)$ the negative sample feature, $D(\cdot, \cdot)$ the cosine distance metric, and α the margin parameter. This semi-hard triplet mining strategy avoids selecting overly easy or overly difficult triplets, concentrating optimization on sample pairs most valuable for model performance improvement.

2.5 Model Training Process

The CNN model was implemented using the PyTorch platform with the following training procedure and parameter settings: Adam optimizer with learning rate of 0.001, triplet loss margin parameter α set to 0.3, batch size of 20, and 798 training iterations per epoch. Data augmentation techniques including random noise addition and slight temporal axis shifting were applied during training. The loss value nearly converged after 10 training epochs. [Figure 8: see original paper] shows the convergence process of loss functions for both training and test sets.

3.1 Implementation of Deep Metric Learning Discrimination

The trained neural network transforms test samples into 128-dimensional feature vectors as deep feature representations of pulse signals. Classification employs the Nearest Prototype Classifier method [19]: (1) Calculate feature vectors for all neutron and gamma pulse samples in the training set. (2) Compute class centroids (prototype vectors): neutron class center C_n and gamma class center C_g . (3) For an unknown test sample x , calculate its feature vector $f(x)$. (4) Compute cosine distances between $f(x)$ and both class centers: $d_n = \cos(f(x), C_n)$ and $d_g = \cos(f(x), C_g)$. Classification follows Equation (5): if $d_n < d_g$, sample x is classified as a neutron pulse; otherwise, it is classified as a gamma pulse.

For visualization analysis, the t-SNE dimensionality reduction algorithm [20] reduces the 128-dimensional feature vectors to 2D space. The resulting feature distribution after t-SNE reduction is shown in [Figure 9: see original paper]. The visualization reveals clear clustering of the two pulse types with distinct boundaries, demonstrating the method's effective feature extraction and representation capability for discriminating neutron and gamma pulses.

3.2 Charge Comparison Method Implementation

To evaluate the performance of our deep metric learning discrimination method, we implemented the charge comparison method as a baseline. This method exploits pulse shape differences between neutrons and gamma rays in organic

scintillators by comparing charge integrated over different portions of the output current pulse [21]:

$$\text{PSD} = \frac{Q_s}{Q_f}$$

In Equation (6), Q_f and Q_s correspond to fast and slow charge components, respectively. Since neutrons and gamma rays produce different waveforms in detectors, their Q_s/Q_f ratios exhibit distinct differences that serve as discrimination criteria [21]. We selected Q_s/Q_f as the discrimination parameter, setting the integration time window from the starting point to 1000 ns thereafter. [Figure 10: see original paper] shows the discrimination statistical results for this configuration.

To quantify PSD algorithm performance, the Figure of Merit (FOM) is defined as [22]:

$$\text{FOM} = \frac{S}{\text{FWHM}_n + \text{FWHM}_\gamma}$$

In Equation (7), S represents the peak separation between neutron and gamma peaks, while FWHM_n and FWHM_γ are the full widths at half maximum of the neutron and gamma peaks in the discrimination results. Larger FOM values indicate better discrimination performance. The FOM value for the results shown in [Figure 10: see original paper] is 1.37.

Since discrimination effectiveness varies with integration window settings, we performed a systematic search to determine optimal parameters. The fast window was swept from 600 to 2400 ns in 200 ns steps to maximize FOM. [Figure 11: see original paper] presents the window traversal results, showing that the charge comparison method achieves optimal performance with a fast window of 1400 ns, yielding an FOM of 1.53.

3.3 Traditional CNN Method Implementation

To further validate the advantages of our deep metric learning approach, we implemented a traditional CNN discrimination method under identical experimental conditions. The network architecture remained the same except the final feature layer was replaced with a two-class output layer using Softmax activation, trained with cross-entropy loss:

$$L = -\frac{1}{N} \sum_{i=1}^N [y_i \log(\hat{y}_i) + (1 - y_i) \log(1 - \hat{y}_i)]$$

In Equation (8), L is the loss value, N the total number of samples, y_i the true label, and $\hat{y}_i$ the predicted output. All other network parameters and training

procedures were kept consistent with the deep metric learning method to ensure fair comparison.

3.4 Performance Evaluation and Comparison

To investigate convergence differences between the two CNN discrimination methods, the preprocessed pulse dataset was input to both models. Experiments revealed that the traditional CNN method required 16 training epochs for near-convergence under identical network parameters and architecture. [Figure 12: see original paper] shows loss value curves during training, demonstrating that the deep metric learning method converges significantly faster than the traditional CNN approach.

To further compare discrimination performance, we employed Discrimination Error Rate (DER) as the evaluation metric [11], defined as the proportion of misclassified samples:

$$\text{DER} = \frac{N_{\gamma \rightarrow n}^{\text{test}} + N_{n \rightarrow \gamma}^{\text{test}}}{N_n + N_\gamma} \times 100\%$$

In Equation (9), N_n and N_γ represent the numbers of neutron and gamma test samples, while $N_{\gamma \rightarrow n}^{\text{test}}$ and $N_{n \rightarrow \gamma}^{\text{test}}$ denote misclassified samples. compares the discrimination error rates of both CNN methods. Although traditional CNN achieves low error rates, the deep metric learning method reduces the error rate by approximately 33%.

To investigate whether deep metric learning can address the generalization deficiency caused by pulse shape variations from front-end electronic parameters and environmental variables, we tested both methods using measured data from reference [23], which provides actual n/ γ mixed radiation fields from a 241Am-Be neutron source. compares discrimination error rates on this measured data. The deep metric learning method reduces the error rate by approximately 70% compared to traditional CNN, demonstrating its effectiveness in solving generalization capability issues.

To comprehensively compare performance across all three methods, we calculated FOM values for both CNN approaches after training. For the deep metric learning method, test set samples were input to the model to obtain feature vector representations. Cosine distances were computed between each sample and reference points for neutrons and gamma rays, defining the discrimination parameter $\text{PSD} = D(\text{sample}, \gamma) - D(\text{sample}, \text{neutron})$. This parameter theoretically ranges in $[-2, 2]$, with $\text{PSD} > 0$ classified as neutron and $\text{PSD} < 0$ as gamma. The PSD range was uniformly divided into 100 bins for statistical counting of neutron and gamma sample distributions.

For the traditional CNN method, test set data was input to the model and the neutron class probability output from the Softmax layer was extracted as

the discrimination parameter PSD. This parameter theoretically ranges in $[0,1]$, with $\text{PSD} > 0.5$ classified as neutron and $\text{PSD} < 0.5$ as gamma. The PSD range was similarly divided into 100 bins for distribution statistics. [Figure 13: see original paper] shows discrimination results for both CNN methods.

compares the performance of all three methods. Testing on 3,986 pulse samples from the test set reveals that traditional CNN ($\text{FOM} = 2.26$) improves by 47.4% over charge comparison ($\text{FOM} = 1.53$), while deep metric learning ($\text{FOM} = 5.32$) further improves by 135.4% over traditional CNN. In terms of computational efficiency, deep metric learning reduces processing time to 1.76 seconds, a 5.9% improvement over traditional CNN (1.87 seconds), indicating that the optimized feature embedding space enables more efficient pulse waveform feature extraction.

For comprehensive performance evaluation, Receiver Operating Characteristic (ROC) curves [24] were analyzed for all three methods. ROC curves graphically illustrate the trade-off between True Positive Rate (TPR) and False Positive Rate (FPR) across all thresholds. TPR and FPR are calculated as:

$$\text{TPR} = \frac{\text{TP}}{\text{TP} + \text{FN}}, \quad \text{FPR} = \frac{\text{FP}}{\text{FP} + \text{TN}}$$

In Equation (10), TP and TN represent correctly predicted positive and negative samples, while FP and FN represent incorrectly predicted positive and negative samples [24]. Here, positive samples denote neutrons and negative samples denote gamma particles. [Figure 14: see original paper] shows ROC curves for all three methods. Superior discrimination methods exhibit ROC curves closer to the upper-left corner, indicating higher classification accuracy and lower false positive rates. The Area Under Curve (AUC) value [24], where values approaching 1.0 indicate excellent performance, confirms that deep metric learning achieves an AUC of 0.991, closer to 1.0 than both charge comparison and traditional CNN methods.

Conclusion

This paper implements an n/γ discrimination method based on deep metric learning and compares it with current mainstream end-to-end neural network classification methods and traditional charge comparison approaches. Results demonstrate that deep metric learning achieves lower discrimination error rates than traditional CNN methods and effectively solves generalization capability issues arising from pulse shape variations due to front-end electronic parameters and environmental variables. Under our experimental conditions, deep metric learning shows substantial performance improvements, with FOM values increasing by approximately 247.7% over charge comparison and 135.4% over traditional CNN. In processing time, deep metric learning offers slight advantages over traditional CNN and significant improvements over charge comparison. The ROC curve for deep metric learning lies closer to the upper-left corner,

indicating higher classification accuracy and lower false positive rates compared to both traditional CNN and charge comparison methods. Moreover, feature extraction based on optimized deep learning frameworks and deep metric learning networks enables embedded deployment of PSD algorithms, providing a novel approach for high-precision particle discrimination technology in radiation detection systems.

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