Study of Inversion Algorithms for γ-Source Number and Coordinate Orientation

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Date: 2025-08-19T00:00:00+00:00

Abstract

Addressing the challenging problem of multi-source radiation field inversion, this study proposes an innovative approach combining Monte Carlo simulation, experimental validation, and convolutional neural networks. A Monte Carlo program is employed to generate 210,000 sets of radiation field data, and convolutional neural networks are applied for the first time to invert the number and coordinates of radioactive sources. Experimental results demonstrate that: for identifying the number of radioactive sources, the identification accuracy of the uniform-coverage detector layout is 24.7% higher than that of the boundary layout, and when combined with the cosine annealing learning rate algorithm, the identification accuracy for 2-4 sources reaches 89.25%; for coordinate inversion, using an innovative strategy of jointly computing center loss and cross-entropy, single-source localization accuracy exceeds 98%, dual-source coordinate inversion accuracy reaches 85.25% (a 5.85% improvement over the baseline method), triple-source peak accuracy reaches 76.13%, and quadruple-source peak accuracy reaches 69.75%. Experimental validation demonstrates that after eliminating environmental background effects, the discrepancy between single-source scenario simulation and actual measurement is $\leq$ 20%, and the error range for dual-source radiation fields is $\leq$ 10%. The engineering practicality of the method for radioactive source localization is thereby confirmed.

Full Text

Preamble

Study of Inversion Algorithms for γ-Source Number and Coordinate Orientation

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Abstract

This study addresses the challenging problem of multi-source radiation field inversion by innovatively proposing a framework that integrates Monte Carlo simulation, experimental validation, and convolutional neural networks. The Monte Carlo method is employed to generate 210,000 sets of radiation field data, and convolutional neural networks are applied for the first time to simultaneously invert the number and coordinates of radioactive sources.

Experimental results demonstrate that in source number identification, the uniform coverage detector layout achieves 24.7% higher accuracy than the boundary layout. When combined with the cosine annealing learning rate algorithm, the identification accuracy for 2–4 sources reaches 89.25%. For coordinate inversion, an innovative strategy that jointly computes center loss and cross-entropy yields single-source localization accuracy exceeding 98%, dual-source coordinate inversion accuracy up to 85.25% (a 5.85% improvement over the baseline method), triple-source accuracy of 76.13%, and quadruple-source peak accuracy of 69.75%.

Experimental validation shows that after removing environmental background effects, the error between single-source scenario simulation and actual measurement does not exceed 20%, while the error range for dual-source radiation fields remains within 10%. These results confirm the practical engineering value of the proposed method for radioactive source localization.

Keywords: Radiation source number inversion, location inversion, CNN methods

1. Introduction

Radiation field inversion reconstruction technology infers the spatial distribution of radiation fields from limited monitoring data through mathematical models and computational methods, holding significant application value in nuclear safety, environmental monitoring, and military domains [1]. This technology utilizes dose data collected by detectors, combines physical models with algorithms to reconstruct the location and activity of radioactive sources, enables three-dimensional radiation field visualization, and provides critical support for personnel protection, nuclear facility optimization, and accident emergency response [2]. In recent years, breakthroughs in artificial intelligence and deep learning have introduced a new paradigm for radiation field inversion, where nonlinear modeling capabilities substantially improve reconstruction efficiency and accuracy in complex scenarios, advancing the development of real-time dynamic reconstruction technology [3].

Current radiation field reconstruction methods fall into two categories: forward simulation and inverse inversion. Forward simulation is dominated by the Monte Carlo (MC) method and the point kernel integration method—the former simulates particle transport through probabilistic models [4–6], while the latter relies on semi-empirical formulas to enhance computational efficiency [7-10]. However, forward methods depend on prior information about radioactive sources, making them ill-suited for engineering challenges involving unknown source terms [2].

Inverse inversion techniques center on interpolation algorithms, including inverse distance weighting (IDW) [11,12], Kriging [13,14], and inverse multinomial quadratic radial basis function (IMRBF) [15], which achieve radiation field reconstruction through spatial correlation modeling. Nevertheless, their accuracy remains limited in strongly nonlinear scenarios. With the advancement of artificial intelligence and maturation of deep learning technology, neural network methods offer new solutions to such problems, exemplified by adaptive BP neural networks [1] and GA-BP hybrid models [16]. However, their generalization capability in multi-source scenarios and the challenge of unknown source identification remain unresolved.

Regarding single-detector localization, Du et al. developed a rectangular scintillation detector achieving 0.1° angular resolution using the KNN algorithm [17], while Sheng et al. proposed a dual NaI scintillation system that optimized detection performance for low-activity sources through a neural network confidence assessment method [18]. These works provide important references for multi-source localization in this study.

This paper proposes a systematic approach based on Monte Carlo simulation and convolutional neural networks (CNN) to simultaneously determine the number and orientation coordinates of unknown radioactive sources in radiation field inversion. By optimizing the detector array layout, introducing the cosine annealing strategy, and fusing the loss function, we enhance model robustness in complex scenarios. The study addresses dual objectives of source number classification and coordinate localization, validated through experiments to ensure data reliability, offering an innovative solution for radiation field reconstruction.

2. Convolutional Neural Networks with Monte Carlo Simulation

Data-driven neural networks demonstrate significant advantages in complex physical field inversion problems by establishing nonlinear mapping relationships between data features and task labels [19]. Traditional artificial neural networks (ANNs) applied to radiation field reconstruction suffer from gradient vanishing and parameter redundancy, primarily because their fully connected structure inefficiently captures spatially correlated features [1]. This study introduces an optimized CNN architecture to radiation field inversion, leveraging its local perception and weight-sharing characteristics to improve feature extraction efficiency. Through iterative calculations of movable convolution kernels, the network achieves high-precision reconstruction of radiation field spatial distributions.

a) Dataset Construction Based on Monte Carlo Simulation

To address experimental data acquisition challenges, Monte Carlo numerical simulation is employed to construct the training dataset. A 10m$×$10m concrete ground environment model is established using MCNP4C software, with 1-4 γ radioactive sources (activity range 1-10 Ci) randomly arranged in a standard atmospheric medium. The platform accurately simulates physical processes such as photoelectric effect and Compton scattering during photon transport by defining spatial structures through geometric raster element cards and configuring medium properties through material raster element cards (Fig. 1 [Figure 1: see original paper]). A multi-resolution dataset containing 200,000 training samples and 10,000 independent test samples is constructed. The detector array is progressively scaled down from an idealized 2,500 nodes (0.1m$×0.1m)toapractical100nodes(1m×$1m) for engineering applications, establishing a transition path from theory to practice through a progressive verification strategy.

Figure 1 Simulation flow of particle transport process

b) CNN Architecture Design and Training Optimization

The CNN system constructed in this study comprises three modular units: data processing, training model, and testing model. The network infrastructure consists of convolutional layers, pooling layers, fully connected layers, and activation functions (Fig. 2 [Figure 2: see original paper]), which overcomes the data processing limitations of traditional fully connected networks through local feature extraction mechanisms. Tailored to radiation field inversion tasks, the network takes dose rate data collected by the detector array as input and outputs the number of radiation sources, their coordinates, and probability distributions.

Figure 2 Schematic diagram of CNN network

Radiation field data obtained from multi-resolution detector arrays exhibit structured characteristics: the absorbed dose rate is normalized to construct a two-dimensional dose matrix, while source position and activity information are recorded and stored in vector form. Through a grid-based coordinate mapping strategy, the continuous coordinate regression problem is transformed into a discrete classification problem, thereby achieving algorithmic unification for source activity prediction and coordinate localization. The dose matrix is stored using FloatTensor in the PyTorch framework, and label vectors are stored using IntTensor. Spatial feature extraction employs a modular convolutional structure (3$×3/2×$2 convolutional kernels). The network comprises the following core components:

- **Feature extraction module**: Cascading convolutional layers (ReLU activation) with a maximum pooling layer progressively compress spatial dimensions and extract features of the radiation field intensity distribution.

- **Classification decision module**: After unfolding through the Flatten layer, a fully connected layer with tanh activation function outputs the source number probability, while the Softmax function outputs grid coordinate classification probabilities. The activation functions are illustrated in Figure 3 [Figure 3: see original paper].
- **Loss function design**: A cross-entropy loss function optimizes the classification task, mathematically expressed as:

$$L_{CE} = -\sum_{i=1}^{C} y_i \log(p_i)$$

where C is the number of classification categories (for 1–4 sources and grid coordinates), and parameters are updated by the Adam optimizer (initial learning rate 0.001). This loss function reflects the model' s ability to respond to step changes in source numbers.

During the test phase, the same data preprocessing as the training set is applied, and the trained model parameters are loaded for forward propagation. The output layer simultaneously generates classification probabilities for the number of radiation sources and grid distribution probabilities for coordinate positioning, with final inversion results determined by probability values. Experiments demonstrate that this architecture effectively adapts to complex physical scenarios with varying detector numbers and dynamic changes in source counts (1–4). Optimization of hyperparameters such as network depth and convolution kernel size for scene adaptability will be discussed in subsequent chapters.

3. Machine Learning Algorithms

This chapter addresses the diversity of radiation fields requiring different detector numbers and the time-consuming nature of Monte Carlo simulations (large-scale calculations under varying physical conditions often require over ten hours or even a full day). A two-stage modeling method based on theoretical formulas and MCNP validation is constructed: the first stage employs dose-rate formulas derived from radiation propagation models [20] (Eq. (3)) to systematically optimize neural network structure parameters; the second stage uses the Monte Carlo dataset to validate and construct the final inversion system after establishing the neural network structure and detector layout scheme.

a) Detector Array Structure Optimization

To balance engineering practicality and algorithmic performance, this section compares three placement schemes using 2,500 detectors (fewer detectors will be discussed in section (b)): centralized layout, boundary-priority layout, and uniform coverage strategy.

Figure 4 [Figure 4: see original paper] Three detector placement schemes (example for dual sources)

The centralized layout places all detectors on a single side of the space (Figure 4(a)) to simulate local distribution characteristics in real scenarios. The boundary-priority layout distributes 2,500 detectors at equal angular intervals on the periphery based on field theory uniqueness theorems (Figure 4(b)). The uniform coverage strategy distributes 2,500 detectors uniformly throughout the space (Figure 4(c)). To accommodate non-uniform arrangements, the standard convolutional layer is replaced with a fully connected layer in the first two schemes to construct baseline models. Each configuration is trained for 1,000 epochs, with dropout layers added to prevent overfitting, and the Tanh activation function combined with cross-entropy loss for training. The trained models are tested on 10,000 independent test sets, yielding the following results (Figure 5 [Figure 5: see original paper]):

Figure 5 Comparison of test results for three detector placement schemes

The results indicate that centralized layouts struggle to effectively distinguish complex interference in multi-source radiation fields. Boundary layouts can improve recognition rates in certain scenarios through mathematical uniqueness theory but exhibit inherent defects in three-source field inversion, likely because boundary data cannot fully characterize internal multi-source superimposed fields. Additionally, air absorption prevents some radiation information from reaching the boundary. Uniform distribution significantly enhances the CNN' s feature extraction capability for multi-source radiation fields, effectively improving algorithmic accuracy and representing the optimal detector placement solution. This scheme validates the superiority of CNNs in radiation field inversion and provides a theoretical basis for engineering practice.

b) Study on Detector Placement Density

To improve the engineering practicality of the radiation field inversion system, this section systematically investigates the number of detectors under the uniform placement scheme using a progressive optimization approach. Experiments with 400, 100, and 16 detectors are constructed to evaluate how different detector densities affect multi-source identification accuracy.

With 400 detectors, the neural network maintains the baseline architecture of double convolutional layers plus fully connected layers. After 1,000 training epochs, the results (Figure 6 [Figure 6: see original paper]) show that despite local accuracy degradation, the overall average accuracy remains at 88.4%, meeting basic application requirements, with training time of 3,204.22 seconds (approximately 53.4 minutes). When detectors are reduced to 100, the control variable method is used to study the effects of input dimension, training batch size, and learning rate on the neural network. The average training time is 1,514.48 seconds (approximately 25.24 minutes), achieving 83.18% four-source accuracy after 1,000 epochs—a decrease of 8.77 percentage points compared to the 400-detector system—while three-source accuracy remains stable at 82.47%. In the 4$×$4 16-detector array experiment, four-source accuracy plummets to 74.88%, confirming that test recognition capability degrades significantly as detector density decreases.

Figure 6 Comparison of test results with different numbers of detectors

Considering both training time and test accuracy, the 100-detector system reduces training time cost by 52.73% while maintaining 82.47% three-source accuracy, establishing a foundation for subsequent experiments.

c) Cosine Annealing Joint Optimization Strategy

As a core hyperparameter in neural network training, the learning rate presents a trade-off: too small values lead to prolonged training and local optima stagnation, while too large values cause parameter instability and prevent convergence. This paper introduces the cosine annealing learning rate scheduler to optimize the training process through dynamic adjustment and validates model generalization using Monte Carlo simulation data.

Cosine annealing, proposed by Loshchilov and Hutter in 2016 [21], simulates a "heating-cooling" process for the learning rate through periodic cosine functions. Specifically, the learning rate gradually decays from an initial value to a preset minimum following a cosine curve, expressed as [22]:

$$\eta_t = \eta_{min} + \frac{1}{2}(\eta_{max} - \eta_{min})\left(1 + \cos\left(\frac{T_{cur}}{T_{max}}\pi\right)\right)$$

where η_{max} is the upper learning rate limit (set to 0.001), η_{min} is the lower limit (set to 0), T_{cur} is the current training step, and T_{max} is the total steps per cycle (set to 100 epochs). This strategy enhances parameter fine-tuning capability through periodic restart mechanisms, enabling the model to escape local minima when approaching optimal solutions. In the radiation source identification task, based on the optimal neural network model from section (b), the cosine annealing scheduler is introduced (period of 100 epochs). Comparison results (Figure 7 [Figure 7: see original paper]) show that the improved group' s loss value decreases significantly faster and exhibits fluctuation characteristics synchronized with the learning rate period.

Figure 7 Comparison of test results with different learning rate strategies

Based on the cosine annealing scheduler, the experimental group achieves accuracies of 98.8%, 97.45%, 92.97%, and 90.23% for 1–4 sources, respectively—significant improvements over section (b) results (98.9%, 92.45%, 82.47%, 83.18%) (Figure 8 [Figure 8: see original paper]). The single-source recognition rate decreases slightly, while multi-source (2–4 sources) recognition improves by an average of 6.51 percentage points, with the greatest improvement in three-source tasks (+10.5 percentage points) and four-source tasks exceeding the 90% threshold for the first time (+7.05 percentage points). Analysis reveals that the cosine annealing restart mechanism effectively mitigates local optimization problems caused by multi-source feature coupling, substantially enhancing multi-source recognition performance.

Figure 8 Comparison of recognition results with and without cosine annealing

d) Monte Carlo Validation

Based on the optimized configuration (uniform detector layout, 100-detector array, cosine annealing period of 100 epochs), MCNP 6.2 simulation generates radiation field data (activity 1-10 Ci) incorporating complex effects such as Compton scattering and ligamentous radiation, trained for 3,000 epochs.

Comparison with section (c) results (Figure 9 [Figure 9: see original paper]) shows that the model converges after 3,000 epochs, with total loss reduced to 114.47 (mean loss 0.185 $\pm$ 0.012), requiring approximately 1.69 hours. The learning rate dynamically spans from 0 to 0.001. On the independent test set, 1–4 source recognition accuracies reach 100%, 98.6%, 84.2%, and 83.1%, respectively. Compared to analytical model training results, single-source recognition improves to the theoretical limit (100% vs. 98.8%), while multi-source recognition decreases: three- and four-source accuracies drop by 6.77–7.13 percentage points, attributed to increased complex physical processes in MCNP data reducing training effectiveness for the same neural network architecture, though accuracy remains acceptable.

Figure 9 Comparison of Monte Carlo and formula-based data-driven approaches

4. Coordinate Inversion of Radioactive Sources

Unlike traditional angle resolution methods based on the KNN algorithm [17] or confidence assessment frameworks for dual-detector systems [18], this study employs convolutional neural networks to process spatial distribution characteristics of multi-source radiation fields, achieving coordinate inversion through a grid-based classification strategy. Using a medium-high activity (MHA) dual-source scenario as an example, the reconstruction area (0–10 m) is discretized into 10 grid labels (Fig. 10 [Figure 10: see original paper]), enabling indirect coordinate regression through classification tasks. Experiments utilize the MCNP simulation dataset to investigate neural network structure optimization for radiation source coordinate inversion before tackling multi-source scenarios.

Figure 10 Schematic diagram of radiation field with 2 radioactive sources

a) Center Loss Optimization

The center loss function, proposed by Wen et al. [23], reduces intra-class differences by constraining the distribution of similar samples in feature space. For input sample x_i, the Euclidean distance to its corresponding class feature center is calculated, defining the center loss function as:

$$L_C = \frac{1}{2}\sum_{i=1}^{m} \|f(x_i) - c_{y_i}\|_2^2$$

where m is the total number of labels (10 classes for classification). Combined with the cross-entropy loss function L_{CE} (see equation (2)), the composite loss function is constructed as:

$$L = L_{CE} + \lambda L_C$$

where λ is the weight coefficient balancing the two losses, set to 0.1 for coordinate classification problems. This function enhances model discrimination capability in boundary regions by forcing similar samples to cluster near feature centers.

The control group uses the cross-entropy loss function from the Chapter III(c) neural network model, while the experimental group employs the fused loss function from equation (6). Results are summarized in Table 1 :

Table 1 Comparison of results with and without center loss function

Comparison Item	Control Group	Experimental Group
Model Architecture	Chapter 3 CNN Networks	Fused Loss Function Model
Training Iterations	3,000 epochs	3,000 epochs
Learning Rate Strategy	Cosine annealing	Cosine annealing
Training Batch Size	40,000 sets (MCNP generated)	40,000 sets (MCNP generated)
Prediction Set Size	2,000 independent data sets	2,000 independent data sets
Loss Function	Cross-entropy	Equation (6) fused loss
Accuracy	77.70%	83.55%

The fused neural network shows a 5.85 percentage point improvement. Figure 11 [Figure 11: see original paper] illustrates scatter plots of unsuccessfully predicted radioactive sources for both cases. Without the center loss function, 446 sources across all 2,000 test sets were misclassified (Figure 11(a)). With center loss constraining feature spatial distribution, this number reduced to 329 (Figure 11(b)), improving overall prediction accuracy by 5.85 percentage points. Comparison of Figures 11(a) and (b) reveals that the center loss function reduces boundary-failure samples, demonstrating its ability to enhance neural network success rates in back-propagating radioactive source coordinates.

Figure 11 Scatter plot of radioactive sources without center loss function (a) and with center loss function (b)

b) Single-Source Localization Error Distribution

Building on these findings, we analyze single radioactive source coordinate inversion using an optimized CNN with two convolutional layers, three fully connected layers after flattening, a cosine annealing period of 100 epochs, and 500 training iterations, employing the fused loss function. The radiation field coordinates are inverted with 10 classification labels, and relevant data are recorded in Table 2 :

Table 2 Single-source localization test results

Indicator	X Prediction	Y Prediction
Train Time	409.03610 sec	431.17472 sec
Train Loss	0.22761 (sum)	0.38279 (sum)
Train Epochs	Convergence	Convergence
Test Accuracy	99.20%	98.90%
Loss Fluctuation	Stable	Higher than x-direction

Both X and Y coordinate predictions exceed 98% accuracy, demonstrating strong inversion capability in single-source radiation fields. Analysis of failed inversion cases (Fig. 12 [Figure 12: see original paper]) reveals significant spatial regularity: X-axis inversion failures (left) occur exclusively at X-direction grid boundaries (e.g., x=2m, 3m, 5m), while Y-axis failures (right) concentrate at Y-direction grid lines. This phenomenon aligns with the conclusion in section (a) that neural network models exhibit reduced sensitivity at radiation field classification boundaries, creating localization ambiguity.

Figure 12 Unsuccessful inversion of X-direction (left) and Y-direction (right) radioactive sources

When the acceptable error range is relaxed from 1 meter to 3 meters (covering three adjacent grids), both X and Y coordinate inversion accuracies improve to 100%. This indicates that boundary blurring issues can be circumvented in practical applications by adjusting accuracy requirements according to actual needs.

c) Sensitivity Analysis Under Multi-Source Interference

This section evaluates neural network localization performance in scenarios with 2–4 coexisting radioactive sources of different activity levels by constructing a multi-source radiation field test model. Using the optimized neural network system from subsection (b), radioactive sources are arranged in descending order of activity. The training set is constructed by collecting X/Y coordinate data. Test results (Figure 13 [Figure 13: see original paper]) show that in two-source scenarios, the first source achieves X/Y localization accuracies of 83.55% and 85.25%, respectively, while the second source achieves 81.8% and 81.85%. When source count increases to three, the first and last sources maintain high accuracies (76.13%/75.97%), but middle source accuracy drops sharply to approximately 50%. The four-source scenario reinforces this trend: first and last source accuracies remain above 68%, while middle two sources fall below 42.2%.

Figure 13 Multi-source coordinate test results

These data reveal two key patterns: (1) Model localization accuracy negatively correlates with source count, with four-source scenario average accuracy decreasing by 32.6 percentage points compared to two-source scenarios; (2) Source activity significantly affects prediction performance—the highest-activity source consistently maintains optimal localization, followed by the lowest-activity source, while medium-activity sources exhibit clear identification bottlenecks. This likely stems from less pronounced dose gradient changes for medium-activity sources, resulting in the neural network extracting weaker feature data from these regions.

Convolutional neural networks demonstrate capability primarily in inverting high-activity and low-activity radiation sources, while identification of medium-activity sources with insignificant dose gradients requires improvement, providing direction for subsequent neural network development.

5. Experimental Results

This chapter presents laboratory radiation field detection experiments to verify that Monte Carlo simulation data remain within acceptable error margins compared to real environments. The experimental procedure involves measuring dose rates across different laboratory scenarios, simulating them using Monte Carlo methods, and drawing conclusions from radiation field dose rate comparisons.

a) Single-Source Radiation Field Validation

Experiments were conducted in a shielded laboratory (background dose rate 0.10 Sv/h) using a RadEye G-10 detector [24] to measure dose rate distributions from a Cs-137 source (activity 1×10^7 Bq). The source and detector were positioned 20–500 cm apart along a straight line (Fig. 14 [Figure 14: see original paper]), recording average and peak dose rates (in Sv/h) at each distance.

Figure 14 Single-source radiation field measurement

MCNP constructed the single-source model with photon energy set to 0.661 MeV (corresponding to the Cs-137 γ decay spectrum) and 1×10^8 particles.

Single-particle dose rates were converted using Eq. (7), with statistical error controlled within 1%:

$$D_{sim} = \frac{D_{MCNP}}{N_{particle}}$$

Comparison of simulated and experimental data (Fig. 15 [Figure 15: see original paper]) shows that at medium and near distances (20–300 cm), error is <10% with high agreement between simulation and measurement. At far distances (450 cm), where dose rates drop to 10^{-2} Sv/h order, maximum error increases due to environmental background interference but is optimized to within 20% after background noise filtering.

Figure 15 Single-source radiation field measurement comparison

b) Multi-Source Radiation Field Validation

High/low activity Cs-137 sources (1×10^7 Bq vs. 1×10^6 Bq) were arranged in a 250 cm × 250 cm area. Latin Hypercube Sampling (LHS [25]) addressed the 6-variable (source and detector coordinates) sampling challenge. Each coordinate variable was divided into 10 layers (25 cm each), with 10 sample sets covering uniform spatial parameter distribution (Fig. 16 [Figure 16: see original paper]).

Figure 16 [Figure 16: see original paper] Multi-source radiation field measurements

Table 3 presents the Latin hypercube sampling results. Monte Carlo simulations maintain 1×10^8 particles with statistical error \$ \$1%. Ten experimental result sets (Fig. 17 [Figure 17: see original paper]) demonstrate consistency: 90% of data points show relative error \$ \$10%; even in high-fluctuation scenarios (experiments 3/4/9) with peak dose rates of 1.0–1.2 Sv/h, error remains stable at -15% to 25%.

Figure 17 Comparison of experimental measurements and Monte Carlo simulation for multi-source radiation field

Experimental results demonstrate that Monte Carlo simulation achieves <10% error in the 20–300 cm range. At longer distances, measurement errors fluctuate significantly due to environmental background interference. Ten experimental sets using LHS comprehensively cover the parameter space, with 90% of data errors \$ \$10%, meeting multi-source scenario requirements. This confirms the engineering practicality of the Monte Carlo method for both single-source and multi-source applications.

6. Conclusions

This study constructs a computational framework integrating Monte Carlo simulation and convolutional neural networks for radiation field inversion with unknown source numbers, achieving high-precision inversion of both the count and spatial location of unknown radioactive sources. Key innovations include:

- Based on the optimal uniform layout criterion, positioning accuracy is verified through 2,500 experiments to be 16.8% higher than traditional boundary layouts.
- Introduction of the cosine annealing joint optimization strategy enables four-source identification accuracy to reach 90%.
- Establishment of a grid-based classification modeling method, combined with the center loss function, reduces coordinate inversion boundary error by 38%, achieving 99.2% single-source and 83.5% dual-source positioning accuracy in 10$×$10 detector arrays.

The study remains limited by high intermediate source localization error (57.8%) and absence of activity inversion in multi-source scenarios. Future work will focus on radioactive source activity inversion using physically constrained neural networks. The current results provide new development ideas for radiation field inversion and offer significant application value for enhancing nuclear emergency response capabilities.

Acknowledgement
This work was supported by the Hunan Provincial Natural Science Foundation of China (2023JJ30625).

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