Study on the Spatial Distribution of Radiation Dose Using Dose Gradient and Least Squares Method

Authors: Jiang, Mr. Lin Jiang, Jiang, Mr. Lin Jiang

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Abstract

In nuclear decommissioning scenarios, the distribution of radiation dose is typically unknown. To understand the current radiation conditions in monitoring operations at nuclear decommissioning facilities, it is crucial to generate continuous visualizations of radiation dose distribution. Current conventional methods involve interpolating between measurement points to obtain continuous radiation dose distributions and predict high-dose regions; however, conventional interpolation methods suffer from low accuracy and poor prediction reliability. Therefore, this paper proposes a method that integrates gradient and least squares, aiming to improve the accuracy of radiation dose interpolation and the prediction precision of high-dose regions. In this study, we utilized the gradient characteristics of radiation dose to determine the direction of high-dose regions, combined with least squares optimization methods to predict high-dose regions, and obtained distribution results through the radiation dose attenuation formula. Comparative experiments with conventional interpolation methods demonstrate that: the proposed method reduces the dose calculation Mean Squared Error (MSE) by 82.1% compared with Kriging interpolation and by 47.9% compared with inverse distance weighting, significantly improving interpolation accuracy. This method is applicable to radiation scenarios composed of gamma-ray (γ-ray) detection point data, can provide technical support for radiation risk assessment and pollution emergency response, and improve the nuclear safety monitoring system.

Full Text

Preamble

On the Spatial Distribution of Radiation Dose Using Dose Gradient and Least Squares Method

Lin-Jiang Jiang, Jun Liu, and Yue Sun
Chengdu University of Technology, Chengdu 610059, China
Xiao-Feng Yang
Chengdu University of Technology, Chengdu 610059, China

In nuclear decommissioning scenarios, the distribution of radiation doses is typically unknown. To understand the current radiation situation during monitoring of nuclear decommissioning facilities, it is essential to generate continuously visualized radiation dose distribution images. The conventional approach involves performing interpolation between measurement points to obtain continuous radiation dose distributions and predict high-dose areas. However, traditional interpolation methods suffer from low accuracy and poor prediction performance. This paper proposes a method that combines gradient analysis with least squares optimization to improve the accuracy of radiation dose interpolation and enhance prediction of high-dose regions. Our approach utilizes the characteristic radiation dose gradients to determine the direction of high-dose areas, integrates this information with least squares optimization to predict high-dose regions, and obtains final distribution results through radiation dose attenuation formulas. Comparative experiments with conventional interpolation methods demonstrate that the proposed method reduces the mean squared error (MSE) of dose calculation by 82.1% compared to Kriging interpolation and by 47.9% compared to inverse distance weighting, thereby significantly improving interpolation accuracy. This method is applicable to radiation scenarios composed of gamma-ray (γ-ray) detection point data and can provide technical support for radiation risk assessment and emergency pollution response, ultimately enhancing the nuclear safety monitoring system.

Keywords: Dose gradient, Least squares method, Radiation scenario

Introduction

In nuclear decommissioning scenarios, collecting dose rate data at various locations and performing spatial interpolation on these measurement points enables observation of dose distribution in the radiation environment and facilitates prediction of high-dose areas. The resulting data can further be used to assess potential impacts of the current scenario and provide core data support for developing subsequent disposal plans. Consequently, research into spatial interpolation methods suitable for radiation scenarios has become an important direction in the field of nuclear safety monitoring.

Current academic and engineering research on calculating radiation dose distribution primarily focuses on two interpolation methods: Kriging interpolation and inverse distance weighting (IDW). Li Hua et al. were the first to apply the Kriging method to reconstruct and visualize radiation dose fields, achieving good reconstruction results albeit with considerable accuracy deviations [**?**]. Jin Guodong and colleagues presented the principles of both inverse distance weighted interpolation and Kriging interpolation, concluding that Kriging inter-

polation generally outperforms inverse distance weighting in most application scenarios [**?**]. Building upon this work, Hu Jifeng et al. introduced the Radial Basis Function (RBF) interpolation method. While RBF generally exhibits inferior overall performance compared to Kriging, its reconstruction accuracy at radiation source positions exceeds that of Kriging [**?**]. Xie Xingwen et al. incorporated network function interpolation into traditional dose rate interpolation methods, using sparsely sampled nodes to reconstruct three-dimensional radiation fields [**?**]. Chi Mingwen improved the Kriging method and conducted comparative studies with inverse distance squared surface interpolation, finding that inverse distance squared interpolation is efficient but less accurate, while the improved Kriging method provides better fitted data but with relatively lower efficiency; overall, Kriging interpolation remains more suitable for practical engineering applications [**?**]. Zhang Biao et al. recognized that radiation fields often contain mixtures of multiple radioactive nuclides, making inversion extremely difficult, and therefore proposed an optimized inverse distance weighting algorithm to reconstruct gamma radiation fields. The reconstruction results obtained using this optimized algorithm showed significantly lower mean absolute percentage error compared to those from the Kriging method [**?**].

The aforementioned methods demonstrate computational efficiency advantages in specific scenarios and can rapidly complete radiation dose distribution predictions. However, they generally exhibit limitations in scenario adaptability. Methods such as Kriging and RBF interpolation perform well for dose inversion within the coverage area of measurement points but tend to produce significant deviations when extrapolating to areas outside this range. Although the IDW interpolation method can achieve extrapolation predictions within a certain range under simple scenarios or with a single radiation source, its interpolation accuracy decreases substantially in complex situations involving multiple overlapping radiation sources and obstacle shielding, and it may even produce incorrect dose distribution predictions. When radiation sources are located at the edge of the monitoring area or in areas inaccessible to detection equipment, existing methods struggle to achieve accurate radiation source localization and dose inversion.

This paper addresses these issues by proposing a radiation dose distribution calculation method that integrates dose gradient analysis with least squares optimization. The method aims to improve the accuracy of radiation dose interpolation in complex scenarios and achieve three-dimensional visualization of predicted high-dose distribution areas. Section 2 explains the principle and implementation process of the method. Section 3 describes comparative experiments between the proposed method and both Kriging and inverse distance weighting methods. The effectiveness of our method is verified through error comparison and image scene comparison, with results analyzed in Section 4. Finally, Section 5 summarizes the main conclusions of this paper.

II. Method Design

As shown in [Figure 1: see original paper], this section focuses on gradient methods and least squares methods, explaining in detail their theoretical basis, computational logic, and specific design ideas through three steps: regional division, gradient method regional constraints, and least squares method simulation calculations.

A. Gradient Method

The radiation dose distribution from a single radiation source in space exhibits distinctive characteristics: a monotonic decreasing gradient outward in all directions from the source center (as shown in [Figure 2: see original paper]). This figure includes three measurement locations labeled 1, 2, and 3, as well as extended lines connecting each pair of locations. By observing these distribution characteristics, key patterns emerge: Positions 1 and 2 fall within different gradient ranges with relatively short spatial separation, and the direction of radiation extending from low to high dose points toward the radiation source center. Positions 2 and 3 belong to the same gradient range with consistent dose attenuation characteristics. Although positions 1 and 3 are in different gradient ranges with relatively large separation, the direction of radiation extending from low to high dose along the line connecting them deviates from the radiation source center.

Based on these rules, the approximate direction of the radiation source can be determined from the magnitude and direction of the gradient. The core principle is that more significant gradient changes indicate regions where radiation shifts from low to high dose in a more concentrated direction, which corresponds to proximity to the radiation source. The calculation of a single gradient magnitude centers on the "dose difference between two points" and the "spatial distance between two points," defined by the following formula:

$$\text{Gradient} = \frac{\Delta D}{(\Delta r)^2}$$

Here, ΔD represents the absolute value of the dose difference between two points, and Δr is the distance between the two points along the connecting line.

However, gradient directions from low to high dose do not necessarily point directly at the radiation source center, and deviations like those shown in the 1-3 line extension are common. Therefore, in most cases, the prediction area can only be narrowed down by calculating multiple gradient rays. The specific formula is as follows:

$$T(D_i) = \max\left\{ \frac{|D_i - D_j|}{(P_i - P_j)^2} \mid i \neq j \right\}$$

where $T(D_i)$ is the set of gradient calculations, D_i is the dose rate (μGy/h) at the i-th measurement point, D_j is the dose rate at the j-th measurement point ($j \neq i$), and P_i and P_j are the spatial coordinates of the i-th and j-th measurement points, respectively. The maximum gradient calculation result between the current measurement point i and all other measurement points serves as the core gradient feature for this point. The direction vector is calculated using:

$$\vec{\alpha}_i = \vec{P}_i - \vec{P}_j$$

where $\vec{\alpha}_i$ is the ray direction vector corresponding to the maximum gradient at the i-th measurement point (direction from the low dose point to the high dose point), and $\vec{P}_i$ and $\vec{P}_j$ are the spatial position vectors of the i-th and j-th measurement points, respectively. The extension direction of this vector provides the candidate orientation of the radiation source.

As shown in [Figure 3: see original paper], gradient methods can efficiently compute the gradient direction in scenarios with a single radiation source. However, in multi-radiation source scenarios such as that shown in [Figure 4: see original paper], multiple sources create overlapping high-gradient regions, causing confusion in ray direction and interfering with determination of the radiation source orientation.

Therefore, before performing gradient evaluation, the data must be preprocessed. High-dose points are segmented while points in low-dose regions are excluded as initial points for gradient rays. Using dose thresholds and spatial distance thresholds as criteria, measurement points are divided into multiple independent high-dose regions defined by:

$$A_i \ni P_j \begin{cases} D_j \geq D_{\text{Threshold}} \\ r_j \leq r_{\text{Threshold}} \end{cases}$$

where A_i represents the i-th high-dose region, P_j is the position of the j-th measurement point, $D_{\text{Threshold}}$ is the preset dose determination threshold that retains only high-dose points for subsequent calculations, and $r_{\text{Threshold}}$ is the preset distance threshold controlling the spatial extent of a single region. When the j-th measurement point satisfies both "dose $\geq D_{\text{Threshold}}$" and "distance to region $A_i \leq r_{\text{Threshold}}$" , the point is assigned to region A_i.

To ensure accurate regional division, the minimum distance from each measurement point to its corresponding region must be updated in real time:

$$r_j = \min\{(P_j - P_i)^2 \mid P_i \in A_i\}$$

where r_j is the minimum distance from the j-th measurement point to its corresponding region A_i, and P_i is any measurement point within region A_i.

Through this preprocessing, the multi-source mixed region in [Figure 4: see original paper] can be divided into two separate high-dose areas (red and blue) as shown in [Figure 5: see original paper], eliminating gradient interference from low to medium doses. Subsequently, calculating the gradient ray direction within each independent area constrains the radiation source localization region.

B. Least Squares Method

The core idea of the least squares method is to quantify the difference between "model-predicted values" and "actual observed values" by defining a "sum of squared errors function,"then find the model parameters that minimize this error. Specifically, this is accomplished by defining an error function that measures the degree of difference between the observed value y and the function $f(x)$ at the corresponding x, typically using the sum of squared errors. For a given set of n data points $(x_1, y_1), (x_2, y_2), \dots, (x_n, yn)$, if the fitting function is $y = f(x)$, then the sum of squared errors S is:

$$S = \sum_{i=1}^{n} (y_i - f(x_i))^2$$

The ultimate goal is to find the set of parameters that minimizes S. In this process, the method optimizes the simulated position of the radiation source by constructing an error function between simulated dose values and actual values, identifying the simulation position corresponding to the smallest error as the optimal simulated position.

Under realistic conditions, radioactive materials are generally stored in containers and pipelines or attached to other objects. Therefore, we introduced scene modeling data as the basis for radioactive material attachment, limiting the simulation range of radiation source locations to mesh-modeled scenes. In the gradient method described in Part A, we obtained a series of gradient rays. After extending these rays from low dose to high dose to the scene-modeled locations, we determined the specific areas of the radiation sources.

Within each area, source data is simulated:

$$D_{1\times i} = |D_1 \ D_2 \ \cdots \ D_i|$$

$$L_{i\times j} = \begin{pmatrix} (P_D(1) - P_{D1})^2 & \cdots & (P_D(i) - P_{D1})^2 \\ \vdots & \ddots & \vdots \\ (P_D(1) - P_{Dj})^2 & \cdots & (P_D(i) - P_{Dj})^2 \end{pmatrix}$$

where $D_{1\times i}$ represents the simulated source dose matrix for each region, $P_D(i) - P_{Dj}$ represents the distance from the simulated source position to the measurement point, and $L_{i\times j}$ represents the squared distance matrix from all simulated sources to all measurement points.

Measurement point data are classified and processed into high, medium, and low dose ranges. In each range, 10% of the data are used as interpolated unknown points, with the remaining data serving as the set of interpolated known points:

$$D_{\text{Known}}^{j\times 1} = \begin{pmatrix} D_1 \\ D_2 \\ \vdots \\ D_j \end{pmatrix}, \quad D_{\text{Unknown}}^{k\times 1} = \begin{pmatrix} D_1 \\ D_2 \\ \vdots \\ D_k \end{pmatrix}$$

A matrix equation is established based on the radiation attenuation function and solved using simulated source dose data:

$$D_{1\times i} \cdot L_{i\times j} = D_{\text{Known}}^{j\times 1}$$

The simulated point dose data for each region are obtained in matrix $D_{1\times i}$, and multi-source joint superposition calculations of the dose at interpolated unknown point positions are performed:

$$D_{\text{Total}}(k) = \sum_{n=1}^{N} D_n \cdot L_n \cdot e^{-\mu_n \cdot d_n(k)}$$

where $D_{\text{Total}}(k)$ represents the dose rate at the k-th interpolation unknown point calculated from the simulated data, N represents the number of simulated sources, D_n is the reference dose rate of the n-th simulated source, L_n is the distance from the position of the n-th simulated source to the k-th interpolation unknown point, μ_n is the linear attenuation coefficient of the medium (related to radiation type and material), and d_n is the thickness of the medium that the radiation passes through.

Finally, the error is calculated using the least squares method:

$$S = \sum_{k=1}^{M} (D_{\text{Total}}(k) - D_{\text{Unknown}}(k))^2$$

where S represents the current error calculation value, M is the number of measurement points, and $D_{\text{Unknown}}(k)$ represents the value of the k-th interpolated unknown point.

Within the gradient-limited area range, the next scene grid unit is identified, the simulation point is updated, and the computation is repeated. After traversing all possibilities, the minimum value is found from the final array S:

$$S_{\text{Best}} = \min(S)$$

where each regional simulated source position corresponding to S_{Best} represents the optimal predicted position of the resulting radiation source.

The best simulated sources obtained from each region are combined and superimposed, with their dose rate attenuation strictly following the inverse square law and medium absorption corrections to calculate the radiation dose rate at unknown points:

$$D_x = \sum_{i=1}^{n} D_i \cdot \frac{r_i^2}{r_x^2} \cdot e^{-\mu \cdot d}$$

where D_x represents the dose rate at any unknown point being measured, D_i represents the dose rate of the i-th simulated radiation source point, n represents the number of simulated radiation sources, r_i represents the distance from the simulated source point to the actual source, r_x represents the distance from the position of the unknown point D_x to the actual source, μ represents the linear attenuation coefficient of the medium, and d represents the thickness of the medium traversed.

III. Experimental Design

The experimental data are sourced from actual measurements at a nuclear waste treatment site, including dose data at measurement points and site point cloud reconstruction data. The experimental environment was built using self-developed 3D radiation field imaging analysis software. The dose rate at measurement points ranges from 0.02 to 0.9 μGy/h. The experiment grouped the data according to the rule of "dividing one dose interval for every 0.1 μGy/h." Within each interval, 10% of the measurement points were selected as interpolation unknown points for comparison and verification, while the remaining 90% served as the training set for subsequent model calculations and performance validation.

To verify the effectiveness of the proposed method, this paper conducts analysis through comparative experiments. The comparison objects include the Kriging interpolation method and the inverse distance weighting method. The evaluation criterion employs cross-validation, with mean absolute error (MAE) and mean squared error (MSE) as the core evaluation indicators. The performance of the Kriging method, inverse distance weighting method, and the method designed in this paper is quantitatively compared. Calculations are repeated five times, with results retained to four decimal places to avoid the impact of sampling randomness. The MSE is calculated based on the average MAE of the five repetitions as the final evaluation criterion. Simultaneously, to explore the error distribution of each method across different dose intervals, unknown interpolation points are ranked from high to low according to their true values. The computed value of each unknown interpolation point is then compared with the actual value, and the absolute errors of the three methods are compared.

To intuitively display the experimental scene, measurement data, and positioning results, image rendering is performed using 3D visualization technology. The specific parameter settings are as follows: the scene adopts a meshing method to construct a 3D model of the experimental site, with a mesh radius set to 0.005 m to balance point cloud density and rendering efficiency while ensuring clear presentation of site structural details; measurement points are marked as point clouds with a point size set to 1.0, making it easy to distinguish measurement points from the scene background and highlight the locations of original data; within the spatial range covered by measurement points and scene data, interpolation calculation points are generated at 0.1 m intervals. Continuous visualization of radiation dose distribution is achieved through volume rendering, allowing intuitive presentation of continuous dose gradients; the transparency of the scene model and measurement points is set to 1.0 to ensure the original scene and data remain clearly visible, while the transparency of interpolation results is set to 0.5 to avoid obscuring original data while highlighting dose distribution trends.

A. Kriging Interpolation Method

Kriging interpolation is based on spatial autocorrelation and achieves optimal unbiased estimation of unknown points through linear weighting of known sample points. Its core calculation formula is:

$$Z(x_0) = \sum_{i=1}^{n} \lambda_i \cdot Z(x_i)$$

where $Z(x_0)$ represents the estimated value at unknown point x_0, λ_i represents the weight of the i-th known point, $Z(x_i)$ represents the attribute value of the known point, and n represents the number of known sample points involved in the calculation.

By combining the spatial attenuation law of radiation dose and quantifying spatial correlation, this experiment matches the weight λ_i to the exponential variogram model:

$$\lambda_i = \text{Nugget} + \text{Sill} \times \left(1 - e^{-\frac{d}{\text{Range}}}\right)$$

The nugget is set to 0 by default, and the sill (the stable maximum value of the variogram) is set to 1.0. The distance d represents the distance from unknown point x_0 to known point x_i. The range represents the maximum distance of spatial correlation. Based on the range between known and unknown points, the distance range of the test data in this study is within 8 meters, so the range is set to 8.0.

B. Inverse Distance Weighting Method

The core logic of inverse distance weighting is that the closer a known sample point is to the unknown point, the greater its weight on the estimated value of the unknown point, which conforms to the attenuation characteristic of radiation dose being "larger when near and smaller when far."The dose estimation formula is:

$$Z(x_0) = \frac{\sum_{i=1}^{n} \frac{Z(x_i)}{d_{i0}^p}}{\sum_{i=1}^{n} \frac{1}{d_{i0}^p}}$$

where $Z(x_0)$ represents the estimated value at unknown point x_0, $Z(x_i)$ represents the actual attribute value of the i-th known sample point, d_{i0} represents the direct distance between known point x_i and unknown point x_0 ($d_{i0} \neq 0$ to avoid division by zero), p represents the distance decay coefficient (set to 2 according to the inverse square law of radiation attenuation), and n represents the number of known sample points involved in the calculation.

C. Gradient and Least Squares Method

Regional Division: In this experiment, the strategy first calculates the maximum dose rate of all known interpolation points and ranks them. Starting from the first known interpolation point as the core, it extends outward by 1.0 m (0.1 times the adaptive scenario range) to form the initial regional boundary. New known interpolation points are then evaluated: if a point falls within an existing regional boundary, a boundary extending 1.0 m from the new point is combined with the original region to form a new regional range, ensuring coverage of all associated high-dose points; if a new known interpolation point falls outside all existing regional boundaries and its dose rate exceeds 0.25 times the maximum dose rate (accounting for a dose attenuation factor of 0.25 at 1.0 m), a new independent calculation region is created centered on this point according to the initial regional rules.

Gradient Calculation: Within each independent region, the candidate range of radiation sources is screened based on gradient directions. Using the maximum dose rate of interpolated known points within the current region as a reference, a screening threshold is set at 0.8 times the maximum dose rate of the current region (the amplification threshold is set for high dose intervals in this study). Only interpolated known points with dose rates exceeding this threshold are retained for gradient calculation, thereby eliminating interference from low-dose points. For each filtered interpolated known point, the gradient value with respect to other interpolated known points in the region is calculated, and the direction with the largest gradient is selected as the core gradient direction. This direction is extended from low dose to high dose until it reaches the boundary of the experimental scenario. The "starting point coordinates" and "boundary endpoint coordinates" of all core gradient rays are collected,

and the maximum and minimum values along the X, Y, and Z axes are extracted. The rectangular space formed by these six extreme values represents the candidate range for radiation sources in the region. Subsequent searches for radiation source locations are carried out only within this range, thereby reducing computational effort.

Radiation Source Localization: Within the candidate range of each area, the simulated radiation source position is iteratively optimized using the least squares method to achieve precise localization. To balance positioning accuracy and computational efficiency, a three-dimensional grid is generated at 0.1 m intervals, with each grid point serving as a candidate simulated radiation source. Combinations of candidate simulated sources from all areas are considered, and the least squares method calculates the sum of squared errors between simulated radiation doses and actual doses at interpolated unknown points. The position parameters of candidate simulated sources in each area are iteratively updated, repeating the error calculation process. Finally, the simulated source position with the minimum sum of squared errors is selected as the final localization result for that area.

Dose Rate Calculation: Using the radiation dose rate attenuation model (Equation 15), dose rate simulation calculations are performed at interpolated unknown points. In this experiment, since material and thickness data of the scene medium are unknown, medium attenuation corrections are not considered, and the linear absorption attenuation coefficient μ is set to 0 (which may result in overestimated calculations). The simulated radiation source is treated as a real source, with r_i set to 1.0 and r_x being the distance from the interpolated unknown point to the simulated radiation source.

IV. Experimental Results

The Kriging method calculation results are shown in and [Figure 6: see original paper], with a calculated mean square error of 0.0715 $(\mu Gy/h)^2$.

. Numerical Experimental Results of the Kriging Method

Number	Average calculated value (μGy/h)	Actual value (μGy/h)	Mean Absolute Error (μGy/h)	MSE $(\mu Gy/h)^2$
				0.0715

The inverse distance weighting method results are shown in and [Figure 7: see original paper], with a calculated mean square error of 0.0206 $(\mu Gy/h)^2$.

The calculation results of the method designed in this paper are shown in [TABLE:??] and [Figure 8: see original paper], with a calculated mean square error of 0.0128 $(\mu Gy/h)^2$.

The absolute errors of the three methods across different dosage ranges are shown in [Figure 9: see original paper].

Based on the MSE quantification results, significant differences exist in the accuracy performance of the three methods. The MSE of the method designed in this study is approximately 82.1% lower than that of the Kriging method and about 47.9% lower than that of the inverse distance weighting method. In terms of performance across different dose ranges, the proposed method shows higher accuracy than both Kriging and inverse distance weighting in the low-dose range; in the medium-dose range, it outperforms Kriging and achieves similar accuracy to inverse distance weighting; in the high-dose range, although calculated results are slightly higher, accuracy still surpasses the other two methods. This indicates that the proposed method effectively improves dose estimation accuracy, with inverse distance weighting performing second best and Kriging showing the lowest accuracy.

The measured point dose data are superimposed in 3D with simulated dose distribution data using experimental software for visualization, with color mapping applied inside a cylindrical barrel that serves as a known container for radioactive materials at the experimental site. The simulation results show high correspondence with the actual scenario, validating the rationality of this positioning method. The visualization follows a color rule where dose ranges from high to low are represented by red → yellow → green → blue. All visualization results use the same viewing angle and observation area to eliminate perspective-related interference in the analysis.

The initial scene is shown in [Figure 10: see original paper], displaying measurement points marked in color against the site background model. Red high-dose measurement points cluster around cylindrical barrel-like objects in the scene, yellow-green medium-dose points spread around the high-dose points, and blue low-dose points are distributed along the site periphery, clearly reflecting the spatial dose gradient characteristics of the measurement data.

After dividing the high-dose regions, gradient rays from low to high dose are drawn as shown in [Figure 11: see original paper]. Gradient rays consist of continuous red dots starting from high-dose measurement points and extending along the direction of maximum gradient to the site boundary. The concentrated directionality of these rays provides an intuitive basis for determining the candidate range of radiation sources.

Within the candidate range defined by the gradient rays, the simulated radiation source points obtained through iterative optimization using the least squares method are shown in [Figure 12: see original paper]. The white marked point in the figure represents the optimal simulated radiation source location.

The final dose distribution visualization results are shown in [Figure 13: see original paper]. The high-dose red region not only fully encompasses the high-dose measurement points but also extends into the interior of the cylindrical container, consistent with the actual location of radioactive material. The

yellow-green medium-dose region covers only the area corresponding to yellow measurement points, and the blue low-dose region is highly consistent with low-dose measurement points, with dose boundaries closely matching the actual gradient pattern.

The dose distribution visualization results using ordinary Kriging interpolation are shown in [Figure 14: see original paper]. The high-dose red areas ($ $0.8 μGy/h) do not align with high-dose measurement points, instead concentrating in blank areas between medium-high dose measurement points. The yellow-green medium-dose areas (0.4–0.6 μGy/h) are excessively spread, encompassing many green and blue low-dose measurement points, which does not correspond to the actual dose gradient pattern. This reflects the failure of this method' s spatial correlation assumption in multi-source scenarios.

The dose distribution results of the inverse distance weighting method are shown in [Figure 15: see original paper]. The high-dose red region accurately covers high-dose measurement points without obvious deviation, and the yellow-green medium-dose region includes only a few blue low-dose measurement points with relatively clear dose boundaries. However, the high-dose region spreads outward from measurement points, covering only the upper surface and top of the cylindrical bucket.

In summary, evaluating from the perspectives of matching degree at different dose measurement points and predictive performance in high-dose regions, the gradient and least squares method designed in this study yields the best results, followed by the inverse distance weighting method, with the Kriging method performing the worst. This result further validates the effectiveness of the proposed method, and the visualization of radiation dose distribution better reflects the characteristics of the actual radiation field.

V. Conclusion

To address the issues of low accuracy and large prediction deviations in traditional interpolation algorithms for radiation dose distribution calculations, this paper proposes a radiation dose distribution calculation method that integrates dose gradient analysis with least squares optimization. Experimental results show that the MSE of the proposed method is 82.1% lower than that of ordinary Kriging interpolation and 47.9% lower than that of inverse distance weighting, fully demonstrating its advantage in dose interpolation accuracy. Furthermore, three-dimensional visualization results indicate that the simulated radiation source points generated by the proposed method can be precisely located inside radioactive material storage barrels, consistent with the physical laws of actual radiation fields. In contrast, the Kriging method produces offset positioning and the inverse distance weighting method only covers barrel surfaces, both failing to reflect the actual spatial positions of radiation sources. This demonstrates the superiority of the proposed method in radiation source prediction accuracy.

Considering both error accuracy and practical features, the above analysis confirms the feasibility and practicality of the proposed method in complex radiation scenarios.

Although the method presented in this paper demonstrates advantages in accuracy and practicality, two areas require further optimization: compared with traditional interpolation algorithms, the proposed method involves more computational steps (excluding error calculation, computation time is 200 ms); when the number of measurement points in high-dose regions is small (< 2), insufficient input data can easily lead to large deviations in radiation source prediction. These issues require further optimization in future work.

VI. Bibliography

[1] Li Hua, Zhao Yuan, Liu Liye, Xiao Yunshi, Cao Qinjian. Research on Kri-based radiation field interpolation and reconstruction visualization theory[J]. Radiation Protection, 2019, 39(6): 475-482. https://qikan.cqvip.com/Qikan/Article/Detail?id=7100685974

[2] Jin Guodong, Liu Yancong, Niu Wenjie. Comparison of distance-weighted inverse interpolation method and Kriging interpolation method[J]. Journal of Changchun University of Technology (Natural Science Edition), 2003, 24(3): 53-57. DOI: 10.3969/j.issn.1674-1374-B.2003.03.017

[3] Hu J, Liu Y, Chen Z, et al. Research on Inverse Reconstruction Method of Radiation Dose Distribution Based on RBF Interpolation[C]. Volume 8: Decontamination and Decommissioning, Radiation Protection, and Waste Management, 2024. https://doi.org/10.1115/icone31-134809

[4] Xingwen Xie, Jiejin Cai, Zhihong Tang. The Reconstruction of 3D Radiation Field Based on Sparse Measurement Data[J], Annals of Nuclear Energy, 2022. DOI: 10.1016/j.anucene.2022.109391

[5] M. Chi, "A Comparative Study Of Improved Kriging And Distance Power Inverse Surface Interpolation," 2020 13th International Conference on Intelligent Computation Technology and Automation (ICICTA), Xi'an, China, 2020, pp. 1-3. DOI: 10.1109/ICICTA51737.2020.00009.

[6] Biao Z, Jinjia C, Shuang L, Xiaomeng L, Yulong Z, Xiaochang Z, Wei C, Yingming S, et al. Optimized Inverse Distance Weighted Interpolation Algorithm for γ Radiation Field Reconstruction[J], Nuclear Engineering and Technology, 2024, 56(1): 160-166. DOI: 10.1016/j.net.2023.09.020

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