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IDW-ResUNet Framework for Ground-Level Radioactive Contamination Estimation Using UAV-Based Airborne Radiation Data

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1. Introduction

Following a nuclear accident, precise estimation of ground-level contamination distribution is essential for environmental recovery and the protection of human lives. Unmanned Aerial Vehicle (UAV)-based airborne radiation surveys enable rapid measurement over wide areas while minimizing human exposure to hazardous regions. One of the major physical factors affecting radiation intensity in outdoor environments is the inverse-square law, which states that radiation intensity decreases proportionally to the square of the distance [1]. Even in environments where only the inverse-square law is considered, reconstructing ground contamination distribution is not straightforward. Typically, the number of airborne observations is far fewer than the number of ground grid points to be reconstructed. Consequently, the linear system expressed as $b = Ax$, where b is the vector of UAV-measured radiation intensities, A is the inverse-square distance matrix between UAV and ground grids, and x is the ground contamination distribution vector, becomes an ill-posed problem with no guarantee of a unique solution [2]. Therefore, ground contamination reconstruction remains mathematically challenging even when only distance-based attenuation is considered. In this paper, we propose an IDW-ResUNet deep learning framework to estimate ground contamination distribution from sparse airborne measurements in a simulated radioactive environment governed by the inverse-square law. This framework provides a foundation for future extensions that incorporate scattering, shielding, and terrain effects.

2. Methods and Results

2.1 Problem Formulation

The forward problem is defined as computing the vector b given the vector x and the matrix A:

$$b = Ax \tag{1}$$

Here, $b \in \mathbb{R}^m$ is the vector of radiation intensities measured by the UAV, $x \in \mathbb{R}^n$ is the ground contamination distribution vector, and $A \in \mathbb{R}^{m\times n}$ is the inverse-square distance matrix between UAV sampling positions and ground grid points, defined as:

$$A_{ij} = \frac{1}{\left\|y_i - p_j\right\|^2 + h_i^2} \tag{2}$$

where y_i denotes the horizontal position of the UAV at measurement i, p_j is the ground grid point, and h_i is the UAV altitude at measurement i. In the forward problem, the computation of b is straightforward, requiring only a single matrix multiplication.

However, reconstructing the ground contamination distribution involves solving the inverse problem of estimating x given A and b. Since $m \ll n$, the solution of x is not unique, and the problem becomes ill-posed. As a result, accurate reconstruction is highly challenging, necessitating the use of approximation techniques.

2.2 IDW-ResUNet Architecture

We employed a ResUNet model, an encoder–decoder architecture with residual connections, to extract features from the input data and reconstruct the ground contamination distribution [3]. The residual connections help reduce information loss during training, thereby improving both the performance and stability of the model. In addition, radiation intensity measurements acquired by the UAV at an altitude of 10 m with 10 m spacing were interpolated using the Inverse Distance Weighting (IDW) method to generate a 128×128 grid representation of the plane at that altitude. The interpolation process transformed the data into a dense representation, which enables the ResUNet model to effectively capture local correlations between neighboring pixels and continuous spatial patterns [4], thereby incorporating richer spatial information. The resulting dense input images were used as inputs to the model, and the outputs were reconstructed 128×128 ground contamination distribution maps.

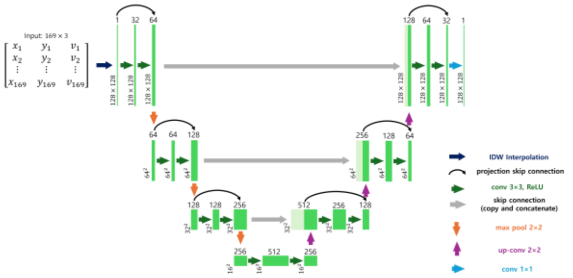
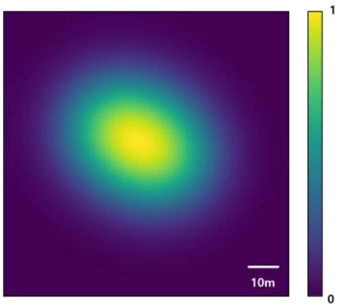


Fig. 1. IDW-ResUNet Architecture

2.3 Dataset Generation and Training

Using a Python-based program, we generated elliptical radioactive contamination distributions in which the intensity decreases with distance from the center. A total of 12,000 synthetic environments of size 128×128 grids were created by varying the center position, rotation angle (θ), maximum spread distance (threshold), and variance of the contamination distribution. In each environment, UAV measurement data were collected at an altitude of 10 m and horizontal intervals of 10 m, with radiation intensity calculated based on the inverse-square law. The entire dataset was divided into 80% for training, 10% for validation, and 10% for testing. Model training employed the Adam optimizer with the Mean Squared Error (MSE) loss function.

(a)



(b)

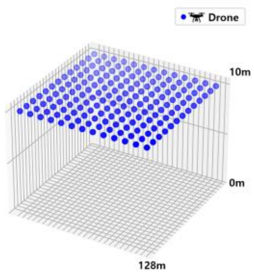


Fig. 2. Examples of (a) a ground truth radiation map and (b) a UAV measurement path.

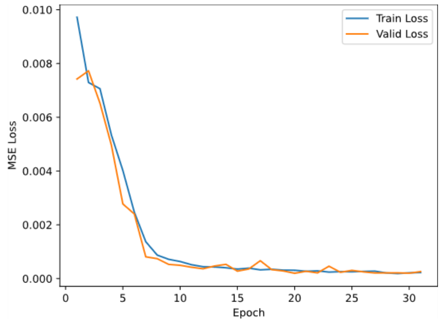


Fig. 3. Training and validation MSE Loss curves over 31 epochs. The similar decreasing trends of training and validation losses indicate that the model was trained stably without overfitting.

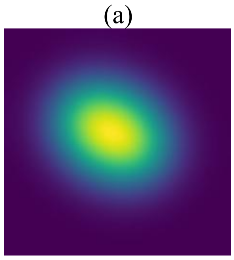
2.4 Preformace Evaluation

For comparison, we considered geostatistical interpolation methods such as IDW and Kriging [6], as well as deep learning models including MLP, CNN, Residual CNN, U-Net, and ResUNet trained with non-interpolated sparse input data. Model performance was evaluated using MSE, MAE, PSNR, and SSIM, which are widely employed image similarity metrics [7]. Among them, MSE, MAE, and PSNR quantitatively measure pixel-wise differences at corresponding locations, while SSIM assesses structural similarity in a manner consistent with human visual perception. The evaluation results demonstrate that the proposed IDW-ResUNet framework—ResUNet trained on dense data interpolated with IDW—achieved superior performance across all metrics compared to conventional methods and other models.

Table I: Error and Score analysis

	MSE	MAE	PSNR	SSIM
IDW	0.060352	0.196762	12.474	0.2768
Kriging	0.018677	0.107056	17.545	0.3444
MLP	0.001275	0.021881	30.362	0.7115
CNN	0.001294	0.021936	30.998	0.6863
Residual CNN	0.001275	0.021797	31.309	0.6722
U-Net	0.003118	0.020981	27.285	0.8958
ResUNet	0.002378	0.018303	28.027	0.9244
IDW-ResUNet	**0.000258**	**0.007237**	**37.768**	**0.9783**

(a)



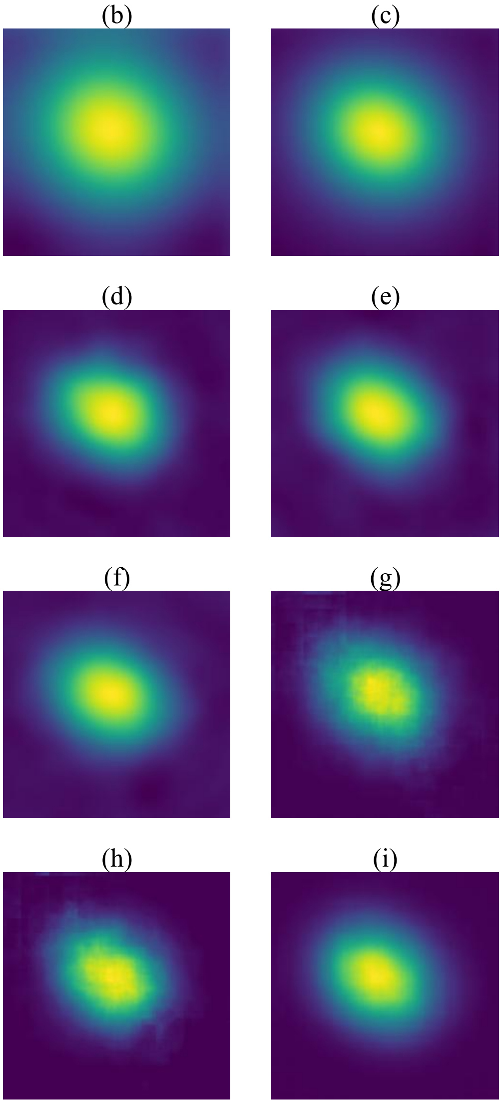


Fig.4 Examples of a ground truth image and estimated images obtained using different methods. (a) Ground truth image; (b) IDW; (c) Kriging; (d) MLP; (e) CNN; (f) Residual CNN; (g) U-Net; (h) ResUNet; (i) IDW-ResUNet.

3. Conclusions

In this study, we addressed the inverse problem of reconstructing ground-level radioactive contamination distribution from UAV-based airborne radiation measurements in an environment governed solely by the inverse-square law. This problem is mathematically ill-posed, lacking a unique solution; to overcome this challenge, we employed a ResUNet-based model. To mitigate the sparsity of airborne data, dense input images were generated using IDW interpolation and applied to the model. Experimental results showed that the proposed approach outperformed conventional methods in image similarity metrics such as PSNR and SSIM. These findings demonstrate the effectiveness of the model in estimating the primary attenuation factor of radiation intensity—the inverse-square law—and suggest its potential applicability in more complex real-world environments where scattering, shielding, and terrain effects are present. Ultimately, this work provides a foundation for future studies integrating multiple physical factors into contamination reconstruction frameworks.

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