Environmental Radiation Monitoring Using a GM Network with AI-Based Anomaly Detection and Source Tracking

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1. Introduction

Environmental radiation monitoring is essential for ensuring radiation safety, regulatory compliance, and emergency preparedness. It involves the continuous measurement and periodic assessment of ambient radiation levels to detect anomalies and potential radiation exposure.

Environmental radiation monitoring employs various detectors, including Environmental Radiation Monitors (ERMs), thermoluminescent dosimeters (TLDs), and Geiger–Müller (GM) detectors. ERMs, which typically utilize high-pressure ion chambers, provide highly accurate real-time dose rate measurements and are widely implemented in fixed monitoring stations. TLDs provide a cost-effective solution for large-scale radiation monitoring. However, they are unsuitable for real-time dose rate measurement, as determining the accumulated dose requires post-processing. In contrast, GM detectors enable real-time dose rate monitoring and are considered a cost-effective detector, making them well-suited for large-scale deployment.

Real-time radiation monitoring with extensive spatial coverage is important near nuclear facilities to enable the early detection of low-intensity radiation anomalies. To achieve this, a cost-effective GM detector module was developed with a simple installation process, allowing for rapid deployment in the field. A total of 50 GM detector modules were deployed at the Korea Atomic Energy Research Institute (KAERI) site, establishing a real-time monitoring network capable of continuous dose rate assessment and high-resolution radiation mapping.

To enhance accident preparedness, convolutional neural network (CNN)-based algorithms were developed for radiation anomaly detection and source tracking using data from the GM network. Analyzing dose rate data from the GM network could be challenging due to non-negligible noise introduced by various environmental factors, including weatherinduced fluctuations, variations in soil moisture levels, seasonal changes in secondary cosmic radiation, and solar cycles [1]. For instance, precipitation can wash radionuclides from the atmosphere, temporarily increasing gamma dose rates [2], thereby complicating the distinction between natural radiation variations and artificial radiation increases. To overcome these challenges, CNNs, which can effectively handle nonlinear patterns and suppress noise, were employed to leverage the spatial distribution and gamma dose rate data, enabling a more robust and precise analysis [1,3,4].

2. Methods and Results

2.1 GM detector module

In this study, a compact GM-based radiation detector module was developed for real-time environmental radiation monitoring. To enable high-resolution radiation mapping across a wide area, the detector employs a compact and cost-effective GM tube, allowing for efficient large-scale deployment. Two types of energy-compensated GM tubes were integrated: a low-dose detector (background to 2 mSv/h) and a high-dose detector (2 mSv/h to 1 Sv/h), both with an uncertainty of $\pm 20\%$.

The module is powered by a 7000-mAh lithium-ion battery, enabling up to three days of continuous operation without solar charging. A 2-W solar panel supports autonomous, long-term operation with minimal maintenance. To optimize power consumption and reduce data transmission load, the detector transmits minute-averaged dose rate values (minimum, maximum, and mean) to the KAERI central server via LTE-Cat M1 communication.



Fig. 1. (a) GM module mounted on a stand with a height of 1 m. (b) Distribution of 50 compact GM detector modules across the KAERI site.

A total of 50 GM detector modules were deployed at the KAERI site, establishing a high-resolution radiation monitoring network (Fig. 1). The average spacing between adjacent detectors was 92.7 m, with distances ranging from 11.6 m to 248.0 m.

2.2 CNN-based Radiation anomaly detection model

Anomaly detection in radiation monitoring involves identifying deviations from normal background radiation, which may indicate radioactive contamination or leakage. To enhance model efficiency and accuracy, the EfficientNet architecture [5] was employed, utilizing MBConv as its primary building block. The model produces a single classification output from a 65 \times 65 pixels dose rate map, using cross-entropy as the loss function.

To train the model, two types of 2D dose rate maps were generated: one representing normal background radiation and another simulating radiation accident scenarios. The KAERI site (approximately 1300×1300 m²) was divided into 20×20 m² grids, forming a 65 × 65 pixels dose rate map. The gamma dose rates measured by the GM network were mapped to the corresponding pixels at the locations of GM modules, while locations without measurements were assigned a value of zero.

The 2D dose rate maps for normal conditions were generated using gamma dose rate data from the GM network, collected between October 2022 and August 2024. In contrast, Monte Carlo simulations were conducted to train the CNN model under abnormal radiation conditions. The dose rates at GM modules were calculated by adding the measured background radiation dose, as the total cumulative absorbed dose is the sum of contributions from both artificial and natural ionizing radiation exposure [6]. For calculated artificial ionizing radiation exposure, GATE Monte Carlo simulations (version 8.2) were performed. In the simulation, a Cesium-137 (137Cs) source, chosen for its high yield in the thermal neutron fission of uranium-235 or plutonium-239, was placed at 23 discrete distances (0.1-200 m) from GM modules. The dose rate-distance relationship was determined based on the inverse square law.

For 2D dose rate maps that assumed the presence of a 137 Cs, the source location was randomly selected from 1235 pixels on a 65 × 65 pixels map while restricted areas at the KAERI site were excluded. The dose rate at each GM module due to the source was then individually computed using the inverse square law, incorporating randomized source placements and activities (10^9-10^{13} Bq).

To train and evaluate the anomaly detection model, 500000 dose rate maps were generated, each randomly either containing or not containing a radioactive source. These maps were then split into 300000 for training, 100000 for validation, and 100000 for testing, with min-max normalization applied to all data. To evaluate the model using the test set, classification performance was assessed using accuracy, precision, recall, F1-score, and the area under the ROC curve (AUC) [7]. The model achieved an accuracy of 0.9999, precision of 1.0, recall of 0.9998, and F1-score of 0.9999, demonstrating high reliability with minimal false positives and false negatives. The AUC was 0.9999, indicating a strong ability to distinguish between normal and anomalous radiation levels.

2.3 CNN-based source tracking model

Following the detection of a radioactive source, accurate source tracking is crucial for identifying its location based on radiation measurements, enabling the implementation of precise safety measures. The source-tracking model generates two regression outputs to predict the latitude and longitude of the source. It utilizes a 65×65 pixels dose rate map as input, and mean squared error is employed as the loss function to optimize performance.

For the proposed CNN-based source-tracking model, 2D dose rate maps were generated and processed using the same method as the CNN-based radiation anomaly detection model, with each map containing a radioactive source. The gamma dose rates at GM modules were computed using the inverse square law, incorporating randomized source placements (1,235 pixels) and activities $(10^9-10^{13} \text{ Bq})$.

To train and evaluate the source-tracking model, 500000 2D dose rate maps were generated. These maps were then split into 300000 for training, 100000 for validation, and 100000 for testing, with min-max normalization applied to all data.



Fig. 2. Example of source tracking results. (a) A 10^{12} Bq 137 Cs source (red dot) is positioned near the center of the KAERI site, while the black x-shaped marker represents the location

estimated by the source-tracking model. The color bar indicates the dose rates calculated for each GM module. (b) A detailed view of the estimated and actual source locations, showing a tracking error of 2.9 m.

To evaluate the model using the test set, the distance between the estimated and artificial source locations was calculated. Figure 2 presents an example of the estimated location and the actual source location. A 10^{12} Bq ¹³⁷Cs source was positioned near the center of the KAERI site. Each GM detector corresponds to a specific position on the 2D dose rate map, where the calculated dose rate is represented by the color bar. The red dot indicates the actual source location, while the black x-shaped marker represents the location identified by the model. The Haversine distance formula was used to convert the distance between these locations from GPS coordinates into meters.

The distance between the estimated and artificial source locations in the test set was evaluated, resulting in an average of 3.44 m with a standard deviation of 1.73 m. A histogram of these distances is shown in Figure 4. The pixel location accuracy, defined as the proportion of test cases in which the estimated pixel position matches the artificial source pixel, was 0.9947, demonstrating the model's high localization performance. These results confirm the effectiveness of the source-tracking model in accurately estimating the location of a simulated radioactive source.



Fig. 3. Histogram of the distances between the estimated and artificial source locations in the test set.

To validate the effectiveness of the source-tracking model, field experiments were conducted using actual radiation sources. An 8.30×10^5 Bq ¹³⁷Cs source was moved across multiple locations at KAERI at an average speed of 33.2 m/min over a period of 86 minutes. While Monte Carlo simulations employed high-activity sources to model accident scenarios, field experiments were conducted using low-activity sources to ensure safety and prevent interference with ongoing environmental radiation monitoring by ERMs and TLDs.

The average distance between the estimated and artificial source locations was 54.73 m, with a standard deviation of 42.90 m. This deviation was greater than the test-set results, primarily due to the low intensity of

the radiation source, which was approximately 10^3-10^7 times lower than the sources used in simulations. Despite these limitations, the ability to track a low-activity source under these conditions suggests that comparable tracking accuracy can be achieved in the event of a high-intensity radiation incident. These findings confirm the practical applicability of the source-tracking model for real-world radiation monitoring.

3. Conclusions

The deployment of the GM network at KAERI was proven to be a cost-effective and efficient solution for real-time radiation monitoring, radiation anomaly detection, and source tracking. Compact batterypowered GM detector modules offer reliable performance in outdoor environments, and the CNNbased algorithm enhances the ability to detect and track radiation sources.

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