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Enhancement of prediction of dose rates distribution using data assimilation

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1. Introduction

In radiation emergency, accurate prediction of the radiation field, or dose rate distribution, is critical for the assessment of radiation exposure and consequent decision-making. While this assessment primarily relies on measurement data, these are not always available, utilization of calculated dose rate distributions in radioactively contaminated areas are necessary. However, dose rate distributions evolve over time and can't be accurately predicted solely based on pre-calculated data sets or specific assumed conditions, particularly in the early stages of an incident where accurate source information is difficult to obtain. Complications arise when attempting to forecast dose rate distribution changes in the event of accidents involving radioactive material leakage due to the unknown types and quantities of radionuclides involved. This study aimed to enhance dose distribution predictions by employing an estimation algorithm developed using the Kalman Filter method. This method is suited for multi-variable calculations such as evaluating dose rate changes in multiple locations, thereby significantly improving the accuracy of dose rate predictions. It also reassessed the effective decay constant at each time step during the application of the Kalman Filter to further refine the predictive model's accuracy.

2. Methods and Results

2.1 Dose prediction model and data assimilation algorithm

This study presents a methodology to predict dose rate changes over time in a radiation emergency scenario, primarily built upon the single component decay model. The principal equation, Eq(1), serves as the foundation of our dose rate prediction model from single component decay model[1]. Here, $X_{i,t}$ represents the log-dose rate at time t at the *i-th* position, $ln(D_{i,t})$, λ_{eff} stands for the effective decay constant.

$$X_{i,t+1} = X_{i,t} - \lambda_{eff} \quad \text{Eq.(1)}$$

To enhance the precision of dose rate and effective decay constant estimations at each time step, we implemented the Kalman Filter method, known for its prowess in minimizing error between model-predicted and measured data. The Kalman Filter process is divided into two steps: a prediction and an update step. In the prediction step, the next time step's prediction value, $X_{i,t+1}$, is calculated based on the previous time step's estimated value, $\widehat{X_{i,t}}$.

$$X_{t+1} = \widehat{X_t} - \lambda_{eff} \quad \text{Eq.(2)}$$

The dose rate distribution X was defined as a $T \times n$ matrix, with T and n denoting the number of time steps and locations (or pixels), respectively. To compute the values estimated by the Kalman Filter, we utilized both the model prediction values and measurements values as shown in Eq.(3).

$$\widehat{X_{t+1}} = X_{t+1} + K_{t+1}(Z_{t+1} - X_{t+1}) \quad \text{Eq.(3)}$$

Where, Z_{t+1} is the measured value matrix, and K_{t+1} is the Kalman-gain which is used to evaluate the estimated value from the predicted and measured values[2]. Eq.(4) calculates Kalman-gain using covariance matrixes of error terms and it is derived to minimize the combined error of two distributions of the model prediction and measurement.

$$K_{t+1} = P_{t+1}H^{\intercal}\,[HP_{t+1}H^{\intercal} + R]^{-1} \quad \text{Eq.(4)}$$

Where, P_{t+1} is the covariance matrix and determined according to following Eq.(5)[3].

$$P_{t+1} = J(F)P_tJ(F)^{\intercal} + Q \quad \text{Eq.(5)}$$

Where, Q is variance matrix and $J(F)$ is the Jacobian of prediction model matrix. F is the transition matrix from the prediction model satisfying $X_{i,t+1} = F(X_{i,t})$.

2.2 test scenario

In this study, a hypothetical scenario was designed to evaluate the developed algorithm. A virtual radioactive contamination map with 100 locations (or pixels) was created, with dose rate values in each pixel randomly sampled between 0 to 100 mSv/hr, serving as the initial dose rate distribution. The effective decay constant, not known a priori, was estimated with an initial guess of 0.7. Measurement data, crucial for prediction, were provided from five out of the 100 locations, sampled from a Gaussian probability distribution with mean values

calculated using the decay model with an effective decay constant of 0.4. The prediction procedure was structured in a total of 10 stages. This test setup offers a comprehensive yet efficient way to evaluate the prediction algorithm.

2.3 Result

The algorithm developed in this study was evaluated by applying it to a test scenario, assessing changes in predicted dose-rates and effective decay constants over ten time steps. An initial dose-rate distribution was provided at all 100 locations, and both predicted and measured values were compared. The algorithm's estimates showed good agreement with the measured data as shown in Fig.1.

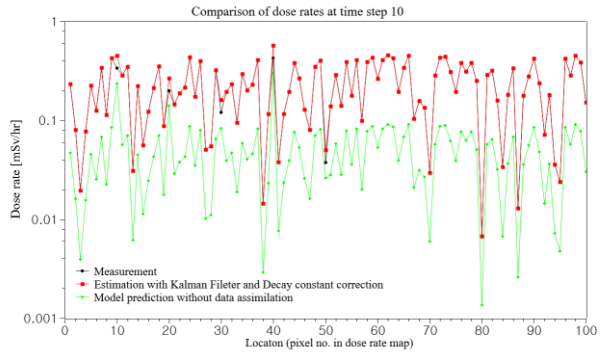

Fig. 1. Comparison of measured values, model predicted values, and estimated values with Kalman filter and effective decay constant correction applied at time step 10 at 100 locations.

The convergence of the effective decay constant was also assessed, demonstrating a trend towards the actual value of 0.4 over time as shown in Fig.2. The error between the initial guess and the actual value was reduced to within 5% by the ninth time step.

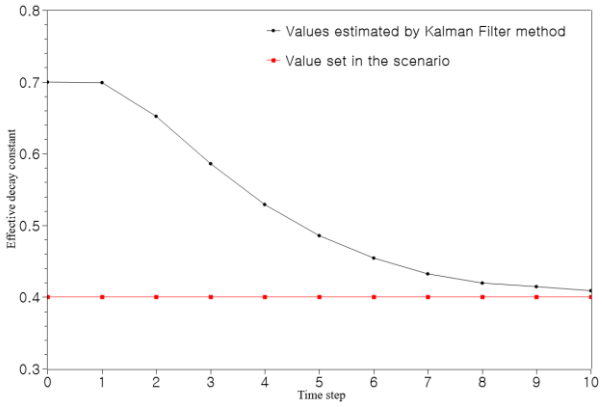

Fig. 2. Estimation of Effective Decay Constant Using Data Assimilation Technique with Kalman Filter.

The study also presented comparisons of model predictions, algorithm estimates, and measurements at five locations where measurement data were provided as C/E values. Fig.3 shows the comparison of C/E values.

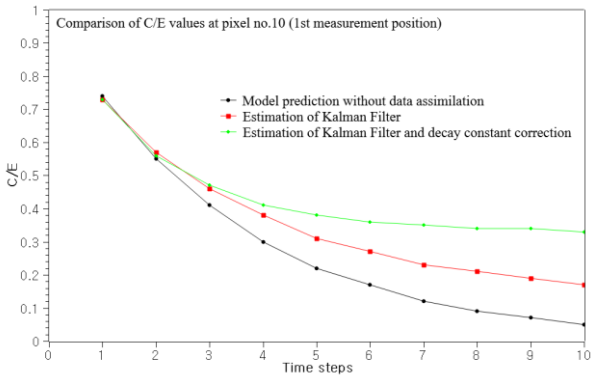

Fig. 3. C/E values during 10 time steps at 1st measurement position (pixel no.10).

This indicated a tendency for model prediction values to deviate from 1 as time steps increase, due to incorrect initial conditions such as inaccurate effective decay constant guesses. This implies that dose-rate values calculated with inaccurate assumptions or information at the time of an accident can significantly increase the difference from actual values (or measured values) over time. The results showed that estimation using the Kalman filter method can reduce the discrepancy with the measured values, and that additional correction of the effective constant can further accelerate the reduction of the error in the estimated value.

3. Conclusions

The application of the Kalman Filter method has been shown to significantly improve the accuracy of radiation dose predictions, by effectively refining estimations and minimizing differences from actual measurements. Importantly, the accuracy of dose rate estimation is further enhanced when a correction for the effective decay constant is integrated with the Kalman Filter. This combined approach swiftly reduces the estimation error, thus improving the reliability of dose assessments in cases of radiological accidents or radiation exposure scenarios.

There are several considerations when using the Kalman Filter approach. Key concerns include the accuracy of prediction model, difficulties in applying to non-linear-system, heavy dependency of initial estimates and uncertainties in error data. In this study a linear dose prediction model was considered, however in real, more complex model might be necessary, then data assimilation methods for non-linear system, such as extended Kalman Filter or particle filter, are required. Initial estimates (or values) concern convergence speed. In this study, decay constant correction was considered to enhance the convergence and the improvement of initial dose data is under consideration in next step. For data error, the initial dose rate values calculated through a sufficient number of Monte Carlo simulation appears

to reasonably follow a Gaussian distribution. However, if the dose prediction model is expanded by considering various factors, additional evaluation for the computational errors is required.

REFERENCES

[1] Kinase, S., Takahashi, T., Sato, S., Sakamoto, R., Saito, K. , 2014. Development of prediction models for radioactive caes ium distribution within the 80km radius ofthe Fukushima Daii chi nuclear power plant. Radiat. Protect. Dosim. 160 (4),318–321. https://doi.org/10.1093/rpd/ncu014.
[2] Kalman, R.E., A new approach to linear filtering and predi ction problem, Journal of Basic Engineering, vol. 82, issue 1, 1960, http://doi.org/10.1115/1.3662552
[3] Ke, L., et. al., A simple data assimilation method to impro ve atmospheric dispersion based on Lagrangian puff model, N uclear Engineering and Technology, vol. 53, issue 7, 2377-2386, (2021)