M.S Thesis Proposal

Autonomous Systems & Control Laboratory
Dept. of Robotics & Mechatronics Engineering, DGIST

Physics-Guided Radiation Field Estimation for Informative and Risk-Aware Path Planning in Radiation Search

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Committee

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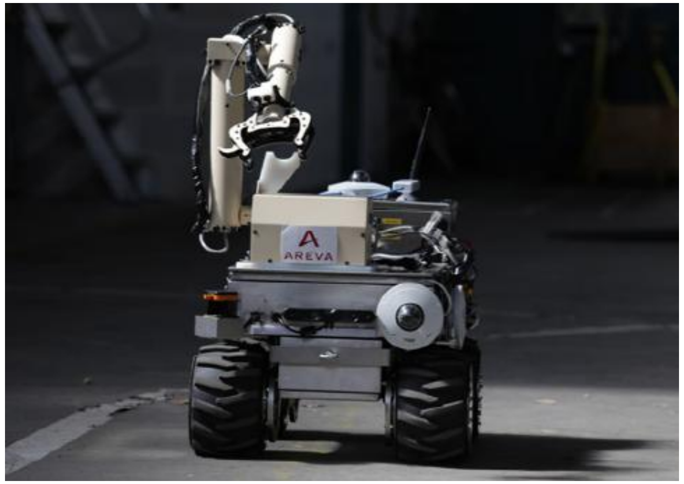
Introduction

Background

❖ Basic Background

- The global demand for **decommissioning** aging **nuclear power plants** is rapidly increasing.
- **Identifying unknown radiation sources** is a critical task during the decommissioning process.
- Human workers face significant exposure risks, leading to the adoption of **mobile robot-based radiation detection** technologies in industrial settings.

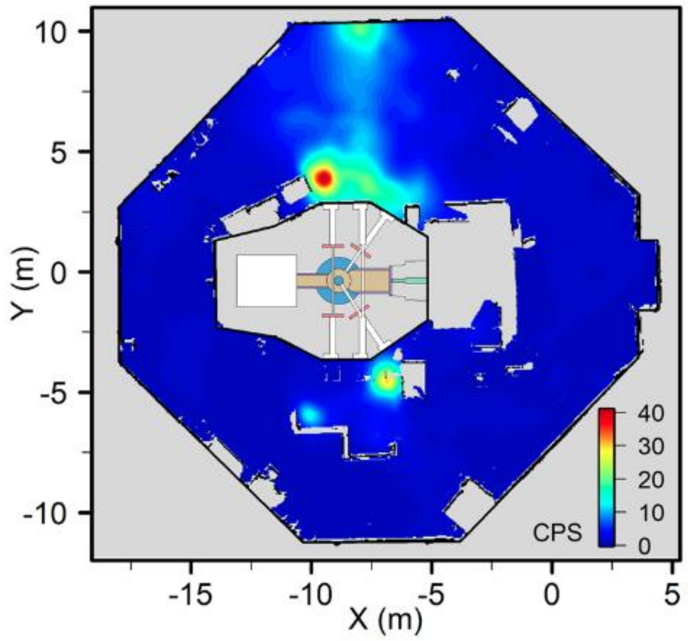


Background

❖ Multi-Radiation Source Search Problem (MRSS)

- **MRSS is the problem of locating multiple unknown radiation sources (position and strength) in an unknown indoor environment, using a mobile robot with limited sensing and movement capabilities.**

- **The mobile robot must:**
  - detect and distinguish multiple point sources.
  - ensure high-confidence localization accuracy.
  - minimize exploration distance and time.



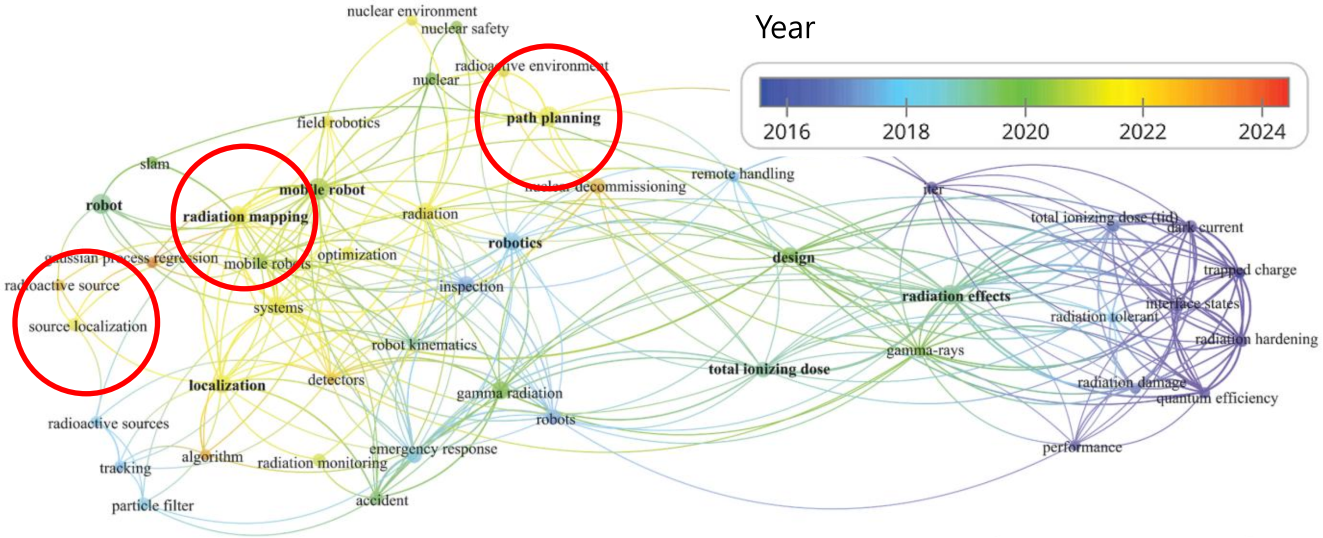
Example of radiation source localization[1]

[1] West, Andrew, et al. "Use of Gaussian process regression for radiation mapping of a nuclear reactor with a mobile robot." *Scientific reports* 11.1 (2021): 13975.

Background

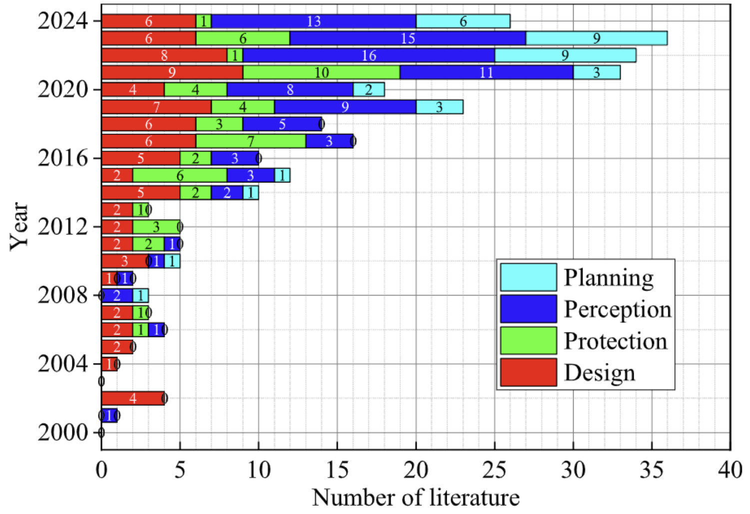
❖ Research trends and activity

- Research on source **localization**, **radiation mapping**, and **path planning** continues to be actively conducted in recent years
- **Perception** and **planning**-related studies account for a **significant proportion** of the overall research



Timeline-overlayed network of keywords co-occurrence[2]

*MRiN : Mobile Robots in Nuclear



The number of literature on design, protection, perception and planning in *MRiN research.[2]

[2] Zhang, De, et al. "Design, protection, perception and planning of mobile robots in nuclear power plants." *Progress in Nuclear Energy* 186 (2025): 105821.

Background

❖ Source localization strategies for radiation source search

Positive / Negative

Source Point Estimation

- **Directly** estimates the **coordinates of radiation sources** based on sensor measurements.
- Works with **small** number of **measurements**
- **Low** computational cost for **few sources**, but **complexity increases rapidly** with **more sources**
- Provides only point estimates with **limited use** for **follow-up actions**

Radiation Field Estimation

- Predicts the spatial **radiation intensity map**, from which source locations can be inferred.
- Requires more data but **can generalize** well even from sparse samples
- Computational **cost is relatively high**
- **Produces interpretable maps**: supports planning, safety assessment, and real-time visualization

Background

❖ Path planning strategies for radiation source search

Positive / Negative

Rule-Based Path Planning	Information-Driven Path Planning
• Defines paths based on **pre-defined rule** sets(zig-zag, spiral path)	• Plan paths based on **measurement outcomes** such as information gain or uncertainty
• Advantages include **low computational cost**	• Computational **cost is relatively high**
	• Highly **sensitive to initial conditions**
• **Limited** flexibility in adapting to **dynamic exploration**	• **Actively considers** the possibility of **multiple radiation sources** during estimation
• Does **not** explicitly perform **online estimation** of the number of sources (mostly inferred through post-processing)	• Plans paths adaptively **online**

Related Works(1/4) : Rule-Based Path Planning

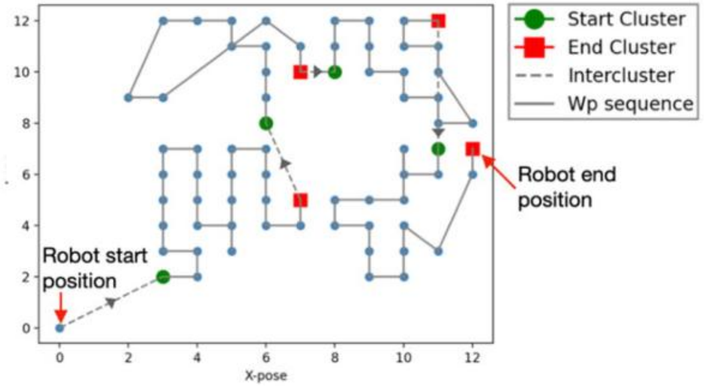
❖ A coverage path planning for autonomous radiation mapping with a mobile robot[3]

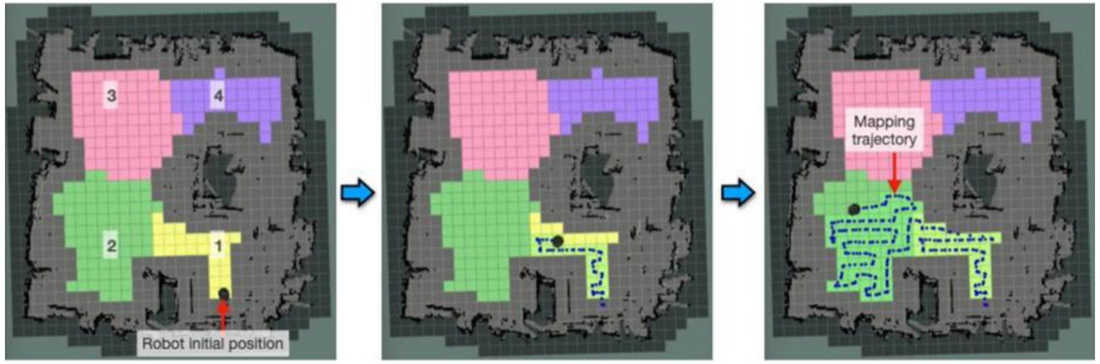
◆ Main Objective

- Plan global paths with dynamic sampling points based on sensor sensitivity and ROI structure
- Overcome limitations of manual sampling point selection

◆ Core Idea

- **Sampling Point Generation**: Grid-based point formulation
- **Waypoint Sequencing & Clustering**: Combine KNN and DFS to generate a continuous visiting path
- **Radiation Mapping & Source Identification**: Apply Inverse Distance Weighting (IDW) to interpolate radiation field over the grid map





Overview and result of algorithm

[3] Abd Rahman, Nur Aira, et al. "A coverage path planning approach for autonomous radiation mapping with a mobile robot." *International Journal of Advanced Robotic Systems* 19.4 (2022)

❖ A coverage path planning for autonomous radiation mapping with a mobile robot[3]

◆ Limitation

- Uses predefined, rule-based path planning, offering limited flexibility to dynamic environmental changes.
- Does not consider overlapping radiation effects.
- In sparse measurement environments, interpolation accuracy significantly degrades, resulting in distorted field estimation.

[3] Abd Rahman, Nur Aira, et al. "A coverage path planning approach for autonomous radiation mapping with a mobile robot." *International Journal of Advanced Robotic Systems* 19.4 (2022)

Related Works(2/4) : Rule-Based Path Planning

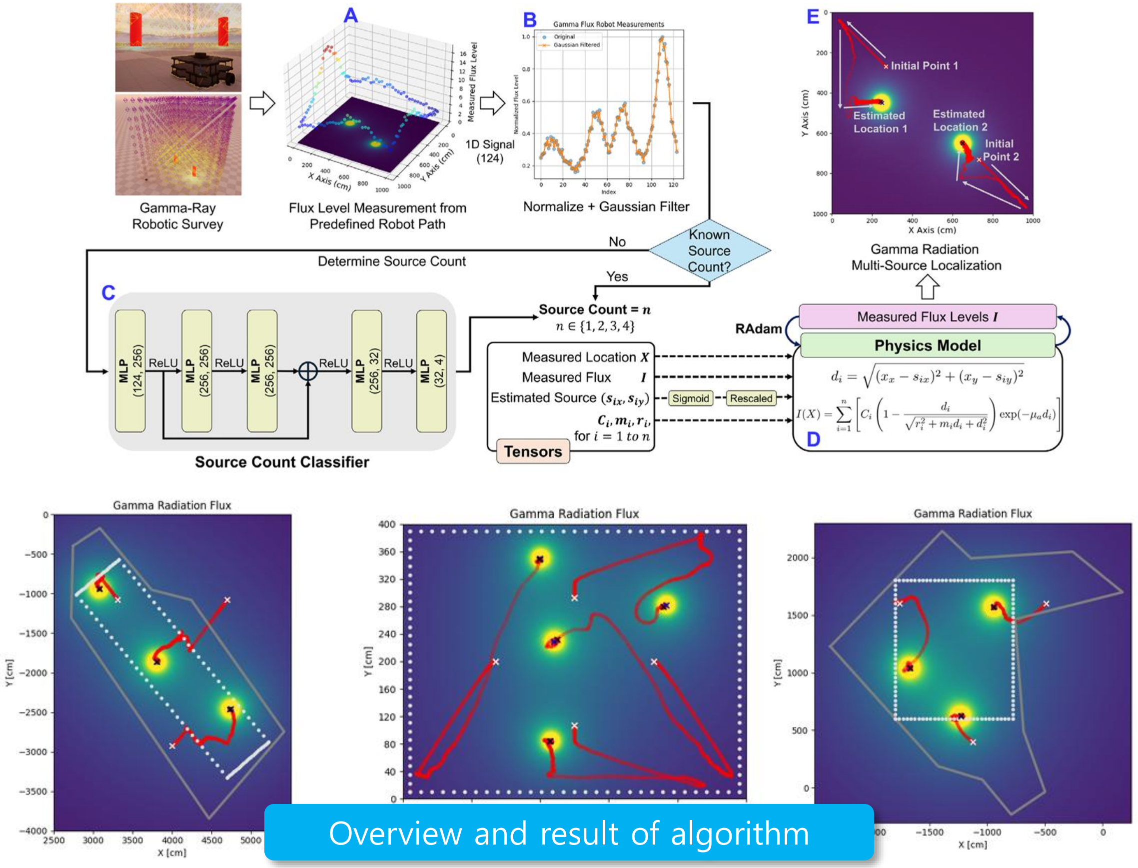
❖ Physics-informed radiation multi-source localization with robotic platform[4]

◆ Main Objective

- Precisely localize multiple unknown radiation sources by following a predefined path and using a physics-informed neural network (PINN)

◆ Core Idea

- **Source Count Classification**: CNN-based predictor for estimating the number of sources
- **Source Localization**: PINN model leveraging measurements and their locations
- **Physics-informed Learning**: Trained with physically simulated data from OpenMC



Overview and result of algorithm

[4] Son, Hojoon, et al. "Physics-informed radiation multi-source localization with robotic platform: H. Son et al." *International Journal of Intelligent Robotics and Applications* (2025): 1-14.

Related Works(2/4) : Rule-Based Path Planning

❖ Physics-informed radiation multi-source localization with robotic platform[4]

◆ Limitation

- Employs predefined, fixed robot paths to stabilize radiation exposure, but this approach is not fully effective and lacks adaptive path planning for improved performance.

- Evaluated using radiation sources with fixed intensity, limiting generalizability to diverse real-world scenarios.

[4] Son, Hojoon, et al. "Physics-informed radiation multi-source localization with robotic platform: H. Son et al." *International Journal of Intelligent Robotics and Applications* (2025): 1-14.

Related Works(3/4) : Information-Driven Path Planning

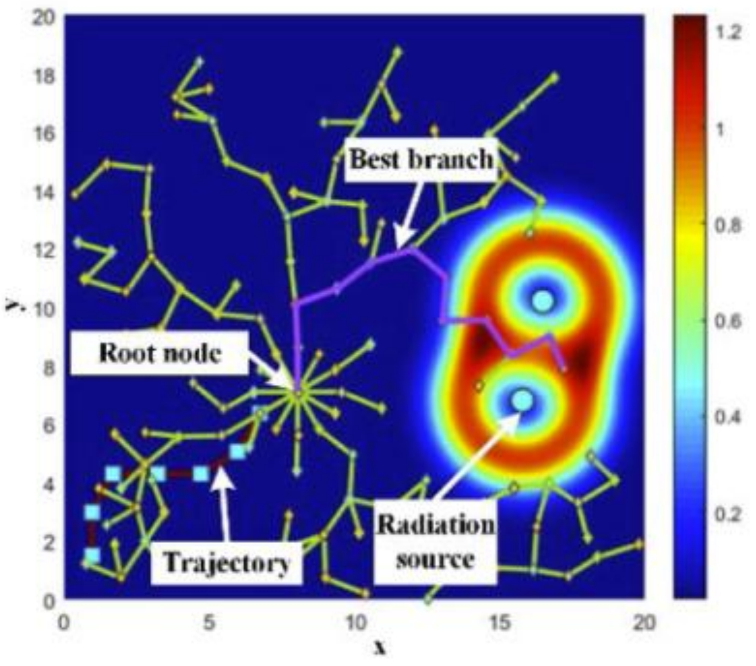
❖ A study of robotic search strategy for multi-radiation sources in unknown environments[5]

◆ Main Objective

- Improve robot navigation strategy for exploring multiple radiation sources without prior information
- Achieve convergence through iterative exploration without requiring a radiation field map

◆ Core Idea

- **Source Localization**: Iteratively update source estimates using a Gaussian Process-based probabilistic model
- **Measurement Selection**: Choose next point via Particle Filter and Mutual Information
- **Multi-Source Handling**: Apply sequential estimation to distinguish overlapping source signals
- **Path Planning**: Optimize path using Genetic Algorithm



Overview and result of algorithm

[5] Bai, Hua, et al. "A study of robotic search strategy for multi-radiation sources in unknown environments." *Robotics and Autonomous Systems* 169 (2023): 104529.

Related Works(3/4) : Information-Driven Path Planning

❖ A study of robotic search strategy for multi-radiation sources in unknown environments[5]

◆ Limitation

- Does not account for overlapping radiation sources, limiting robustness in complex scenarios.
- Cannot accurately predict the number of sources when the Intensity Difference Ratio (IDR) exceeds 50%
- Since ease of navigation was not considered, there is a high possibility that the path explores routes unrelated to the robot's actual state

[5] Bai, Hua, et al. "A study of robotic search strategy for multi-radiation sources in unknown environments." *Robotics and Autonomous Systems* 169 (2023): 104529.

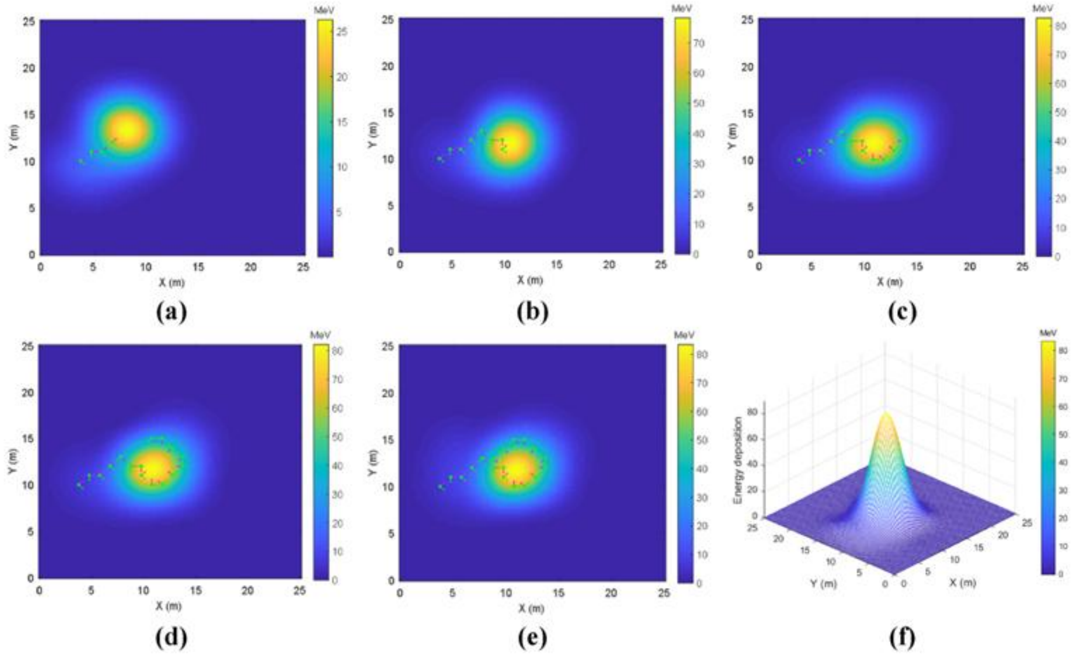
❖ Autonomous exploration for radioactive sources localization based on radiation field reconstruction[6]

◆ Main Objective

- Implement an end-to-end framework for radiation field reconstruction and source localization using sparse measurements
- Enable autonomous path planning for UGVs based on information-driven strategies

◆ Core Idea

- **Exploration**: Guide robot using gradient ascent on radiation intensity
- **Local Search**: Use circular paths near high-radiation areas
- **Field Reconstruction**: Predict dense field via Gaussian Process Regression (GPR)



Overview and result of algorithm

[6] Hu, Xulin, et al. "Autonomous exploration for radioactive sources localization based on radiation field reconstruction." *Nuclear Engineering and Technology* 56.4 (2024): 1153-1164.

Related Works(4/4) : Information-Driven Path Planning

❖ Autonomous exploration for radioactive sources localization based on radiation field reconstruction[6]

◆ Limitation

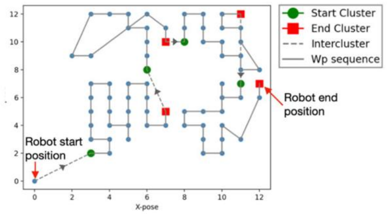
- Has difficulty separating sources when they are spatially close, leading to inaccurate localization.
- Does not model overlapping radiation effects, which may interfere with field reconstruction.
- Lacks a global exploration strategy — the robot focuses locally around detected sources, limiting full-area coverage.

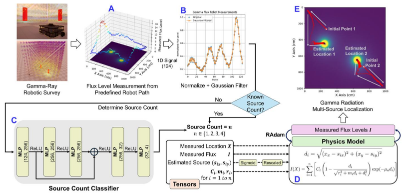
[6] Hu, Xulin, et al. "Autonomous exploration for radioactive sources localization based on radiation field reconstruction." *Nuclear Engineering and Technology* 56.4 (2024): 1153-1164.

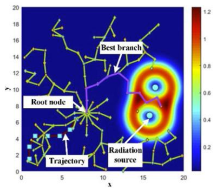
Related Works

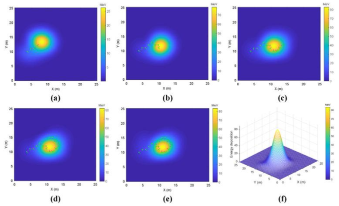
❖ Comparison

Positive / Negative









	Abd Rahman, Nur Aira, et al.	Son, Hojoon, et al.	Bai, Hua, et al.	Hu, Xulin, et al.
Source search method	Radiation field estimation	Source point estimation	Source point estimation	Radiation field estimation
Source diversity (value of source)	Different height	Same height	Different height (limited)	Different height
Allowing radiation overlap effects	No	Yes	No	No
Path planning method	Rule-Based	Rule-Based	Information-Driven	Information-Driven
Risk avoidance strategy	No	Yes (static)	Yes (dynamic)	Yes (dynamic)
Global exploration	Yes	Yes	Yes	No

Problem Statement

❖ Problem setup

◆ Given:

- A known 2D environment $\Omega \subset R^2$
- An unknown number $N_s \in \{1, 2, 3, 4\}$ of stationary radiation sources
- A mobile robot equipped with a radiation sensor that can measure at discrete positions $\{x_i\}_{(i=1)}^{T} \subset \Omega$
- Each source contributes radiation intensity $\mathrm{r(x)}$ following a physical decay model[7]

$$\mathrm{r(x)} = \sum_{\mathrm{j=1}}^{\mathrm{N_s}} \frac{A_j}{|x - s_j|^2}$$

◆ where:

- $x \in \Omega$: measurement location
- s_j: location of the j-th source
- A_j: intensity of the j-th source

[7] Ristic, Branko, Mark Morelande, and Ajith Gunatilaka. "Information driven search for point sources of gamma radiation." *Signal Processing* 90.4 (2010): 1225-1239.

Problem Statement

❖ Research focus

The mobile robot must:

- **predict a dense radiation field** $\hat{r}(x)$ **from sparse measurements**

- **plan a path** $P = \{x_1, x_2, ..., x_t\}$ **that:**
  $argmax \sum_{x_i \in P} W(x_i)$ **subject to minimal path length and exposure constraints**

  - use the predicted field to generate a weighted map $W(x)$ combining:
    - Radiation risk
    - Information gain
    - Traversability (i.e., motion efficiency)

Proposed Method

Original Contributions

❖ Physics-Guided Radiation Field Estimation for Informative and Risk-Aware Path Planning in Radiation Search

[OC 1]

A radiation field predictor using Mask-Attention based ConvNeXt[8] + U-Net[9] trained on synthetic data with physics guided loss.

[OC 2]

Multi-Objective RRT[10] Planning: Uses risk, information gain, and traversability maps to guide weighted path selection.

[OC 3]

Simulation and real-world Experiment showing improvements in prediction accuracy, information efficiency, and exposure reduction.

[8] Liu, Zhuang, et al. "A convnet for the 2020s." *Proceedings of the IEEE/CVF conference on computer vision and pattern recognition*. 2022.

[9] Ronneberger, Olaf, Philipp Fischer, and Thomas Brox. "U-net: Convolutional networks for biomedical image segmentation." *International Conference on Medical image computing and computer-assisted intervention*. Cham: Springer international publishing, 2015.

[10] LaVallе, Steven M., and James J. Kuffner. "Rapidly-exploring random trees: Progress and prospects: Steven m. lavalle, iowa state university, a james j. kuffner, jr., university of tokyo, tokyo, japan." *Algorithmic and computational robotics* (2001): 303-307.

Approach

❖ System overview

1. Drive & Measure radiation value

2. Estimate radiation field

3. Make sampled path candidates

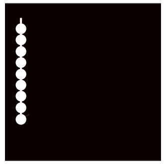
4. Calculate weighted map

5. Select *n*-step path

Approach

❖ System overview

Step 1. Drive & Measure radiation value



Initial strategy

First 10 step should move forward to get initial measurement

Sparse radiation measurements

Sparse radiation map

$R_{input} \in R^{H \times W}$

Measure value by each position

$D_{meas} = \{(x_i, r_i)\}_{i=1}^{T}, x_i \in R^2, r_i \in R$

Step 2. Estimate radiation field

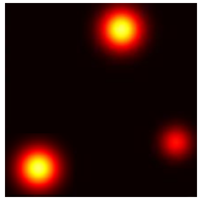
PGNN based radiation prediction model

Dense predicted radiation field map

$\hat{r} = f_\theta(R_{input}) \in R^{H \times W}$

Uncertainty map

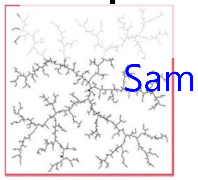
$\sigma_{\hat{r}} \in R^{H \times W}$



<Radiation field map>

<Uncertainty map>

Step 3. Make sampled path candidate



Sampled path candidate based on RRT

Step 4. Calculate weighted map

1. Risk Layer

$$L_r(x) = 1 - \frac{\hat{r}(x) - \min(\hat{r})}{\max(\hat{r}) - \min(\hat{r})}, L_r \in R^{H \times W}$$

2. Information Gain Layer

$$L_i(x) = \begin{cases} \|\nabla \hat{r}(x)\|, & if\ \hat{r}(x) > \tau_r \\ \sigma_{\hat{r}}, & otherwise \end{cases}$$

3. Traversability Layer

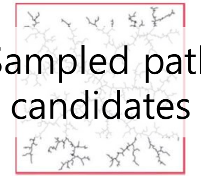
$$L_t(x) = \exp(\alpha \cdot \|x - x_0\| - \beta \cdot |\angle(x - x_0, \theta_0|)$$

+

Weighted map

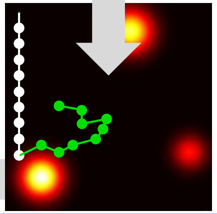
$$W_{map}(x) = \lambda_1 L_r(x) + \lambda_2 L_i(x) + \lambda_3 L_t(x)$$

Step 5. Select *n*-step path

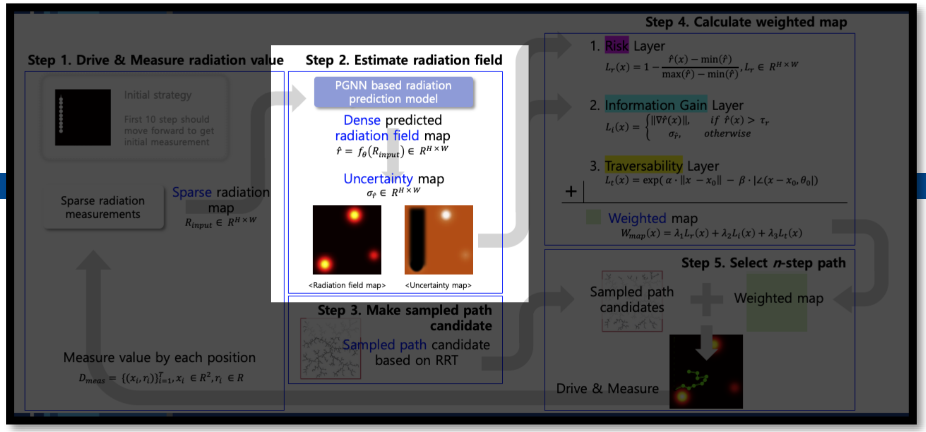


Sampled path candidates

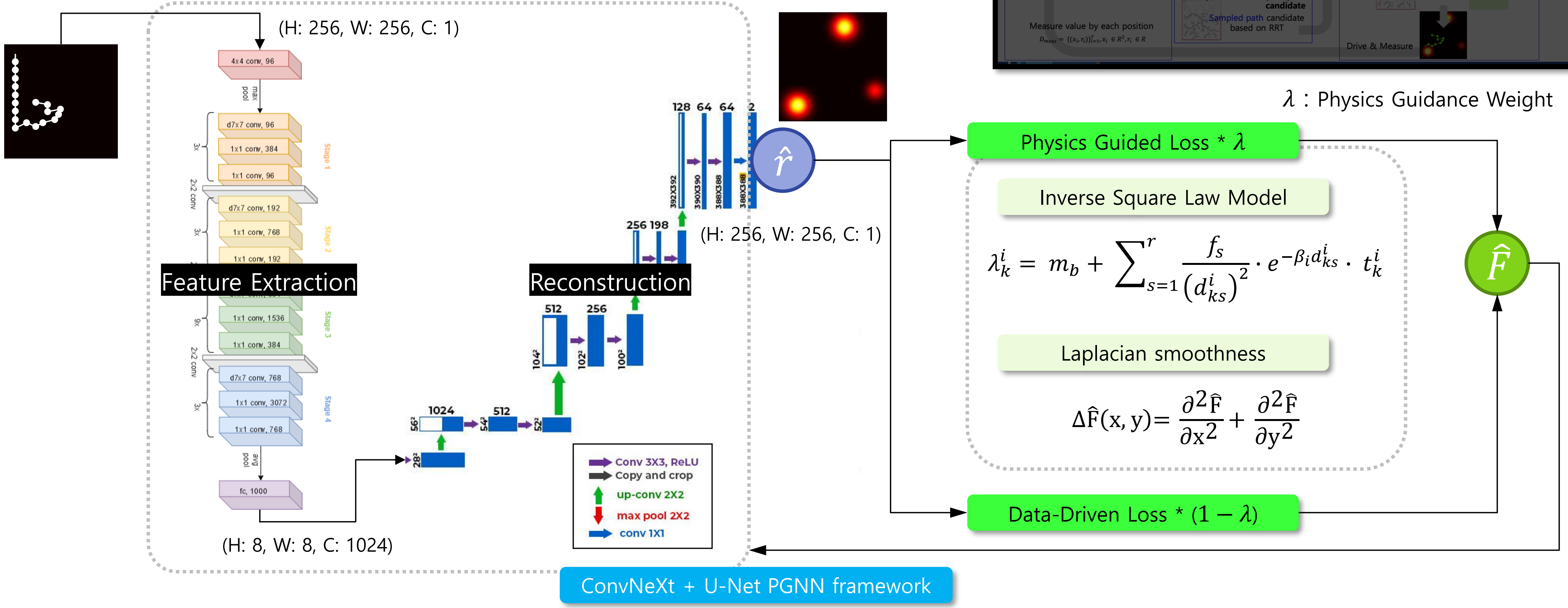
Weighted map



Approach



❖ PGNN[11] based radiation prediction model



[11] Daw, Arka, et al. "Physics-guided neural networks (pgnn): An application in lake temperature modeling." *Knowledge guided machine learning*. Chapman and Hall/CRC, 2022. 353-372.

Approach

❖ Inverse square low model

$$\lambda_k^i = m_b + \sum_{s=1}^{r} \frac{f_s}{\left(d_{ks}^i\right)^2} \cdot e^{-\beta_i d_{ks}^i} \cdot t_k^i$$

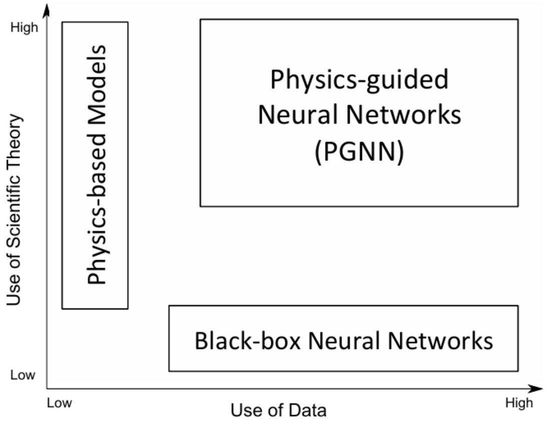
Term		Explanation
λ_k^i	**Expected Measurement (Mean)**	Radiation count expected at sensor i at time t_k
m_b	**Background Radiation**	Naturally occurring radiation present throughout the environment
$\sum_{s=1}^{r}$	**Source Contributions**	Combined radiation effect from all sources present simultaneously
f_s	**Source Strength**	Intensity of source s (stronger sources produce higher readings)
d_{ks}^i	**Distance**	Distance between sensor i and source s
$\left(d_{ks}^i\right)^2$	**Distance Attenuation**	Radiation weakens with distance (inversely proportional to the square of distance)
$e^{-\beta_i d_{ks}^i}$	**Air Attenuation**	Reduction in radiation due to absorption while traveling through air
t_k^i	**Exposure Time**	Duration of the measurement (longer exposures result in higher counts)

Approach

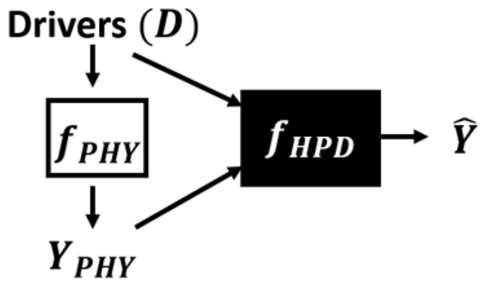
❖ Physics-guided Neural Network (PGNN)

◆ What is PGNN?

- A neural network framework that incorporates physical laws into data-driven models to produce scientifically consistent and generalizable predictions
- Limitations of existing approaches:
  - **Black-box NN**: Accurate but often physically inconsistent
  - **Physics-only models**: Less generalizable, computationally expensive



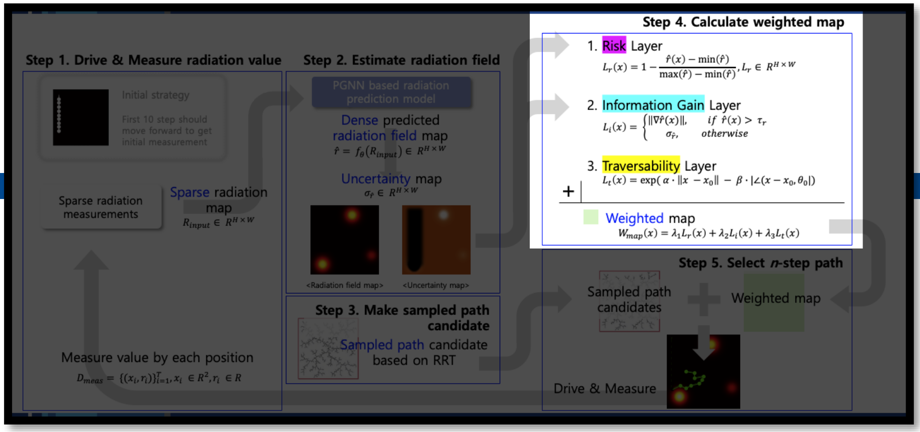
A diagram showing where PGNN stands among data- and physics-driven knowledge discovery methods



$$\arg\min_{f} \underbrace{Loss(\hat{Y},Y)}_{\text{Empirical Error}} + \underbrace{\lambda\, R(f)}_{\text{Structural Error}} + \underbrace{\lambda_{PHY}\; Loss.PHY(\hat{Y})}_{\text{Physical Inconsistency}}$$

Illustration of a basic hybrid-physics-data (HPD) model

Approach



❖ Weighted map generation

◆ Risk Layer

- Assigns lower risk to areas farther from predicted source locations
- Encourages source-avoidant navigation to reduce contamination risk

$$L_r(x) = 1 - \frac{\hat{r}(x) - \min(\hat{r})}{\max(\hat{r}) - \min(\hat{r})}, L_r \in R^{H \times W}$$

◆ Information Gain Layer

- Gradient-Based Gain: Assumes regions with sharp changes in predicted field hold more valuable information
- Uncertainty-Based Gain: Estimates prediction variance; prioritizes measurements in high-uncertainty areas

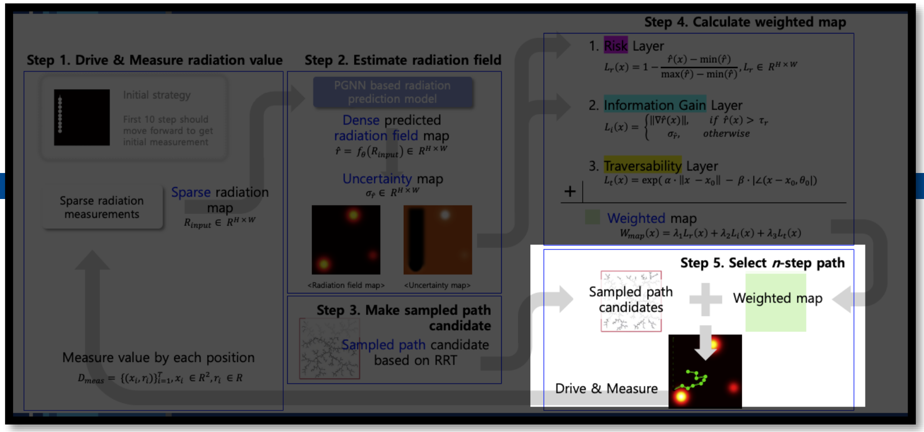
$$L_i(x) = \begin{cases} \|\nabla \hat{r}(x)\|, & if \ \hat{r}(x) > \tau_r \\ \sigma_{\hat{r}}, & otherwise \end{cases}$$

◆ Traversability Layer

- Encourages paths that minimize overall measurement time
- Guides the robot toward coordinates with minimal turning and longer forward progress

$$L_t(x) = \exp(\alpha \cdot \|x - x_0\| - \beta \cdot |\angle(x - x_0, \theta_0|)$$

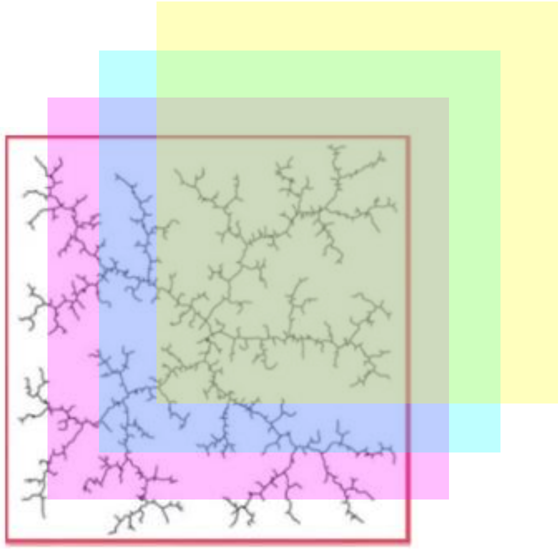
Approach

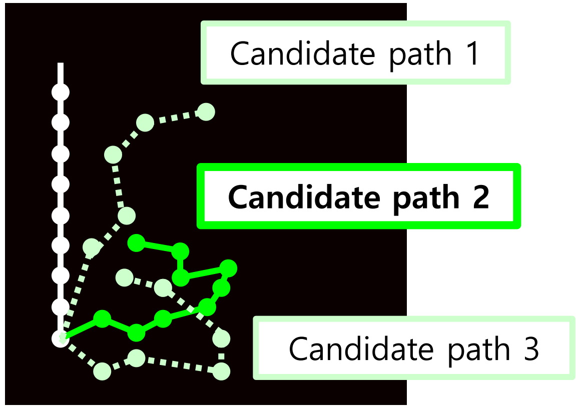


❖ Weighted map based path planning

- **Generate candidate paths** using an RRT-based approach
- Select the *n*-step path with the highest projected value on the weighted map
- Execute movement and perform radiation measurement
- Update the radiation field and weighted map
- Re-plan and repeat the process

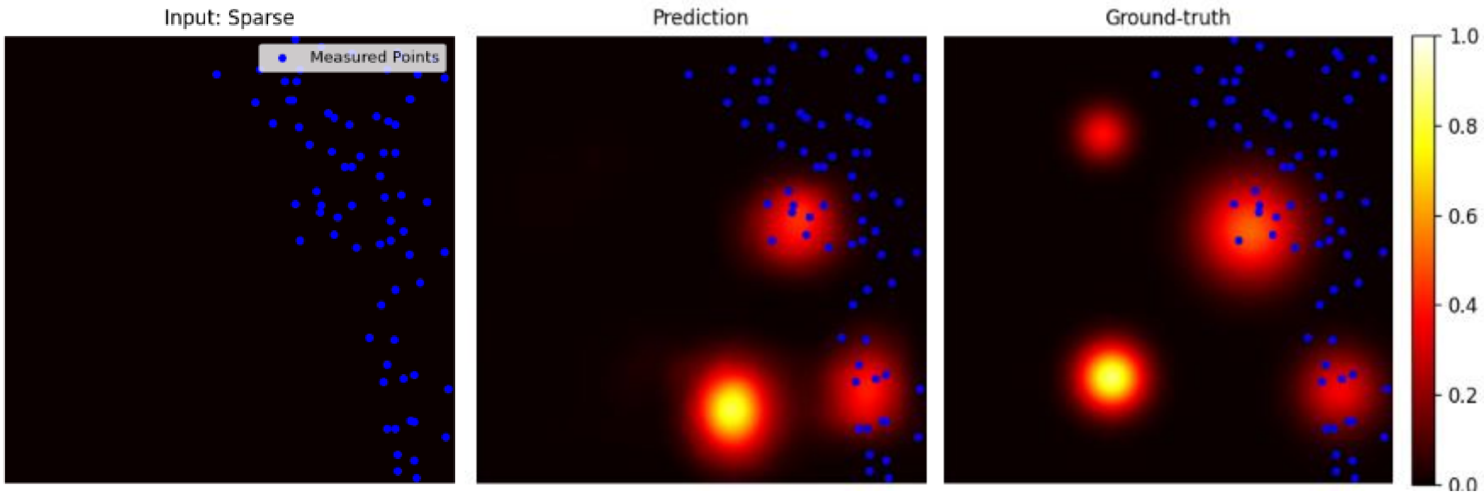
Risk layer
Information gain layer
Traversability layer

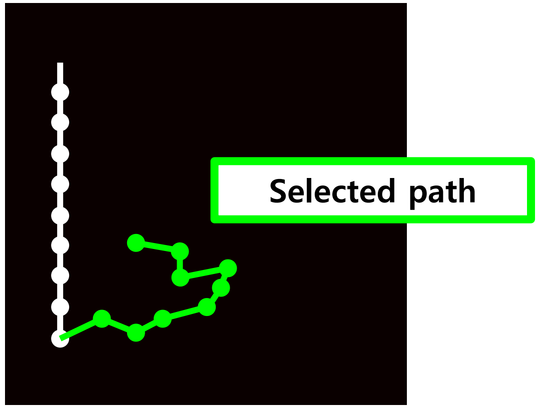




Expected Result

❖ Expected Results of Prediction and Path Planning





$$\tilde{P} = \{(x_1, y_1, \theta_1), (x_2, y_2, \theta_2), \dots, (x_n, y_n, \theta_n)\}$$

Expected Result of radiation field prediction model(Step 2)

Expected Result of path selection(Step 5)

Experiments

❖ Assumption

◆ Environment Assumptions

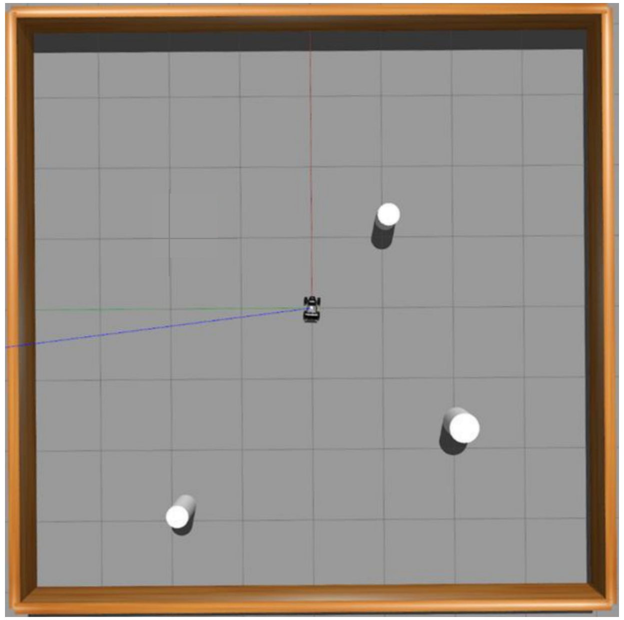
- The environment is a 10m × 10m 2D indoor square map
- Dynamic obstacles are not considered

◆ Radiation Source Assumptions

- Radiation sources are fixed near the ground and do not move over time
- Each source is modeled as a point emitting radiation with circular attenuation

◆ Robot & Measurement Assumptions

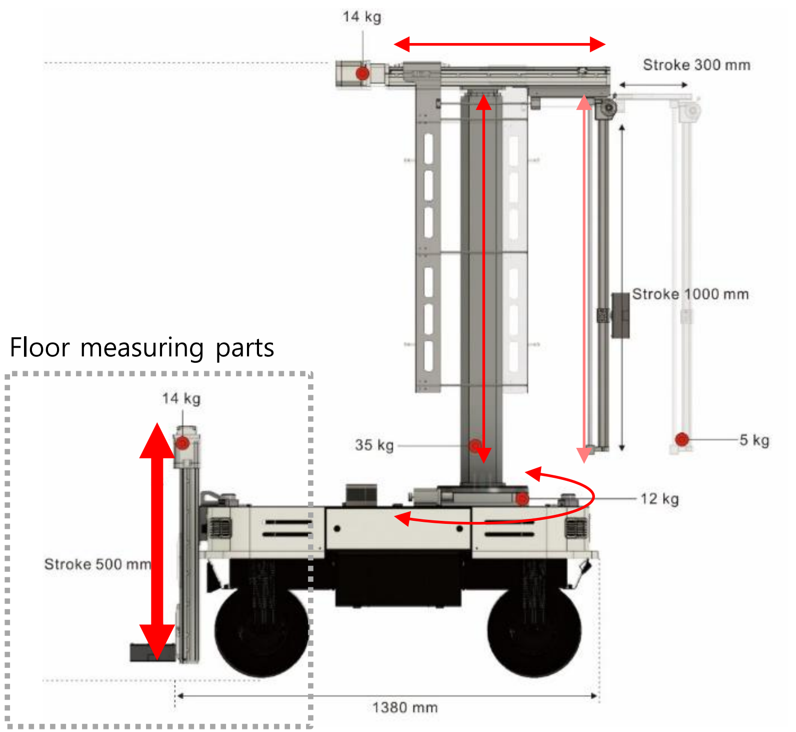
- The robot follows a move-stop-measure pattern, stopping at specific locations to measure
- Measurements are scalar radiation intensity values with noise
- It is assumed that passing directly over a radiation source poses a contamination risk



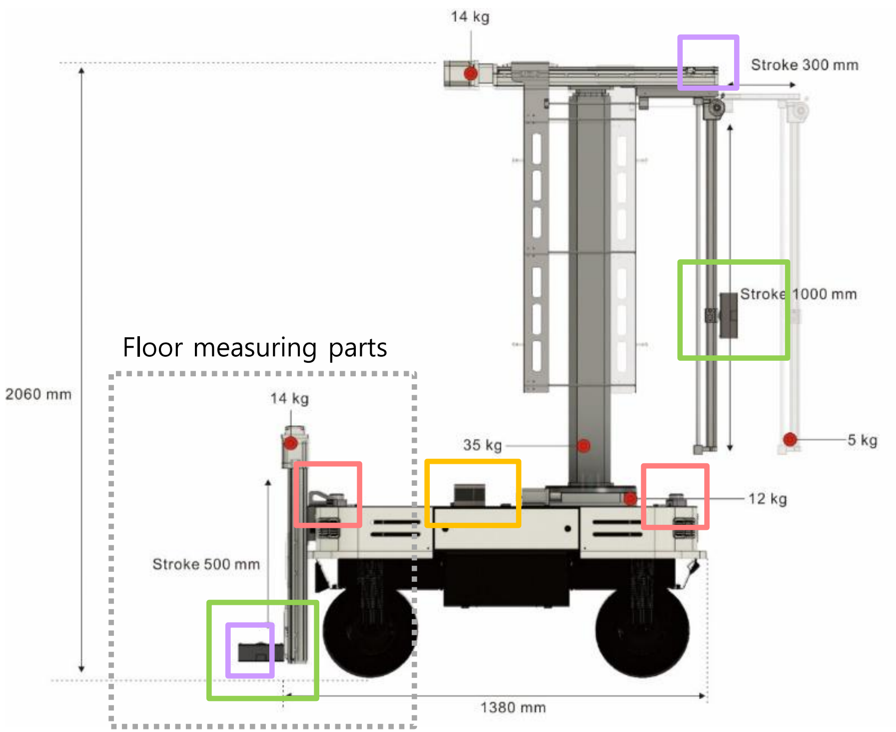
Simulation environment setting

Experiments

❖ Platform



Basic concept design (drive system)



Radiation sensor
3D LiDAR
2D LiDAR
ToF sensor

Basic concept design (sensor system)

Experiments

❖ Environment

Actual robot

10m * 10m indoor test field

Experiments

❖ Performance evaluation of radiation field predictor

◆ Radiation Field Prediction Accuracy

- RMSE (Root Mean Squared Error)
- SSIM (Structural Similarity Index Measure)

◆ Source Detection Performance

- Localization Error (Distance between predicted and true source positions)
- Detection Rate (Proportion of correctly detected sources)

◆ Effect of λ (Physics Guidance Weight)

- Analyze model performance under different λ values controlling physics loss influence

Experiments

❖ Performance evaluation of path planner

◆ Navigation Efficiency Evaluation

- Total Number of Measurements comparison
- Total Measurement Time comparison

◆ Ablation Study on Weighted Layers

- Evaluate performance when each layer is deactivated (risk, information gain, traversability)
- Analyze results with varying contribution ratios for each weight layer

Future Works To Be Done

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❖ Plans

◆ ConvNeXt + U-Net PGNN Structure Validation - in August

- Evaluate physical consistency using masked prediction and Laplacian loss
- Compare performance against baseline GPR and U-Net on sparse-to-dense radiation field inference

◆ Highest-Weight Path Planning (Simulation) - in September

- Simulate path planning on synthetic fields with varying source distributions
- Analyze efficiency in terms of measurement count and coverage time

◆ Highest-Weight Path Planning (Field Test) - in September

- Deploy robot in real environments using PGNN-predicted weight maps
- Verify robustness of path execution under partial observability and real noise

Questions & Answers

Thank you