Robot Path Planning for Monitoring Dynamic Environment by Predictive Uncertainty Minimization Using Gaussian Process Regression

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1 Introduction - Background

- **Environmental Monitoring for Achieving Digital Twin**
  - disaster response, smart building management , precision agriculture
- **Challenges:**
  - require continuous and accurate data collection in wide areas to make informed decisions
  - fixed sensors (limitation)
    - time-consuming, resource-intensive, impractical for certain environments
- **Mobile robot**
  - flexible and efficient: move along a route given by path planning strategy to collect data in real-time

1 Introduction - Traditional Path Planning

- **Focused on collecting information**
- **Maximize information gain within limited resources**
  - time, path length, or energy
- **Not consider the dynamic environment**
  - the environmental features may change during the robot's movement
  - the past observations may be no longer useful, and new observations may be required to follow the real-time changes

Uncertainty

old observations are still close to the current actual value over time?

1 Introduction - Objective

- **Continuous Enviromental Monitoring**
  - **Minimize Uncertainty Levels**

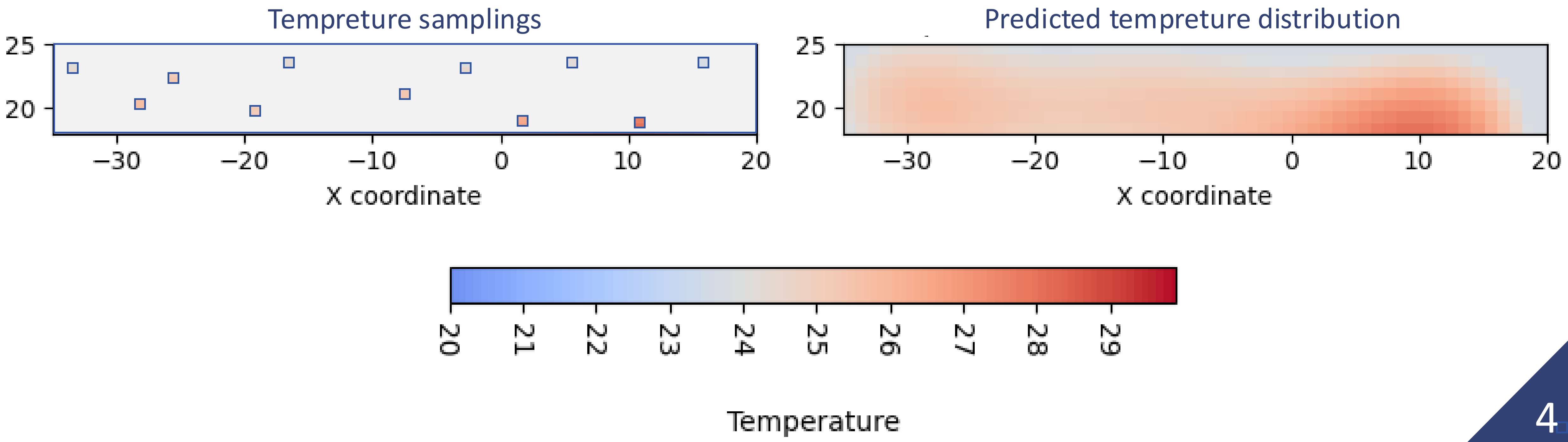
    Ensure that the uncertainty of environmental predictions remains consistently low during the robot's movement
  - **Accurate Predictions**

    Maintain the prediction error within an acceptable range compared to actual environmental values
  - **Sustainable Monitoring**

    Enable continuous monitoring, allowing the system to start and stop at any location and time as needed

2 Key Concepts - Gaussian Process Regression

- **Gaussian Process Regression (GPR)**
  - models environmental features and provides probabilistic predictions along with uncertainties



3 Proposed Method - Spatio-Temporal GPR

- **Spatio-Temporal GPR(ST-GPR) Model**
  - Spatio-Temporal Kernel Function

$$k_{ST}\left(\mathbf{x}_i, \mathbf{x}_j\right) = \sigma_0^2 \cdot \exp\left(-\frac{\left\|\mathbf{z}_i - \mathbf{z}_j\right\|^2}{2 \cdot l_{\text{space}}^2}\right) \cdot \exp\left(-\frac{\left|t_i - t_j\right|}{l_{\text{time}}}\right)$$

space decay rate

time decay rate

  - Mean value and uncertainty

$$\mu(\mathbf{x}^*) = k_{ST}(\mathbf{x}^*, \mathbf{X}) K^{-1} \Delta y(\mathbf{Z}, T)$$

$$\sigma^2(\mathbf{x}^*) = k_{ST}(\mathbf{x}^*, \mathbf{x}^*) - k_{ST}(\mathbf{x}^*, \mathbf{X}) K^{-1} k_{ST}(\mathbf{X}, \mathbf{x}^*)$$

  - Global uncertainty $\sum_{\mathbf{z} \in \mathbf{Z}} \sigma\left(\{\mathbf{z}, t\}\right)$

3 Proposed Method - Predictive Uncertainty Minimization

- **Predictive Uncertainty Minimization(PUM)**

$$U(\mathbf{X}, \mathcal{C}) = \int_{t}^{t+H} \sum_{\mathbf{z} \in \mathbf{Z}} \sigma\left(\{\mathbf{z}, t\} | \mathbf{X}, \hat{\mathbf{X}}_{\mathcal{C}}\right) dt$$

$$\mathcal{C}^* = \underset{\mathcal{C} \in \{c^N\}}{\arg\min} U(\mathbf{X}, \mathcal{C})$$

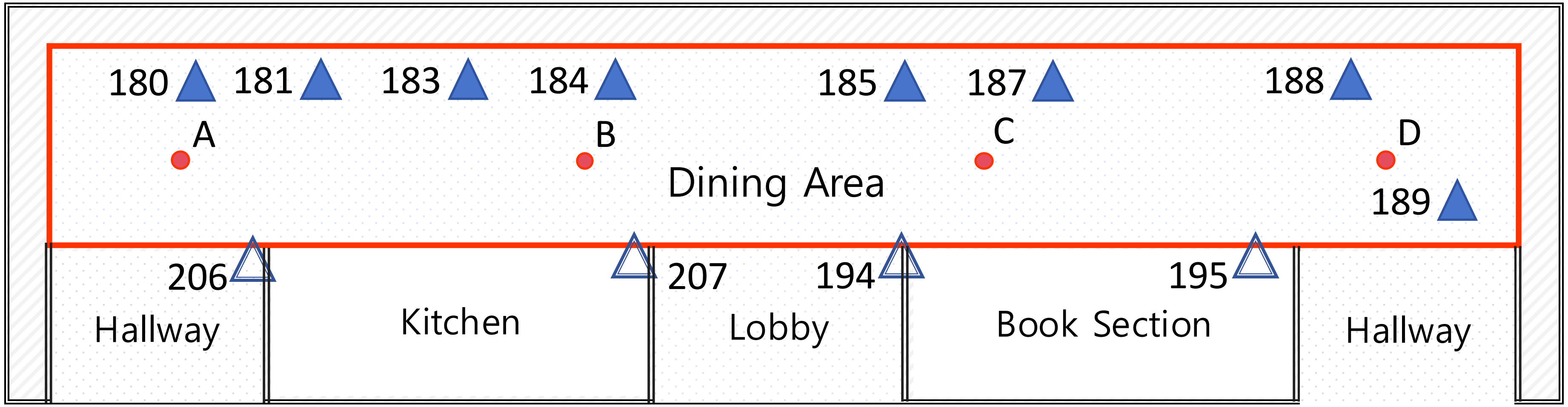
Where N x △T = H

scanning interval of sensor

- Solve the optimization problem over a time horizon
- Adaptive control based on predicted future states (only the first step of the solution is implemented)

4 Experimental Setup - Dataset

- **Real-world temperature data**

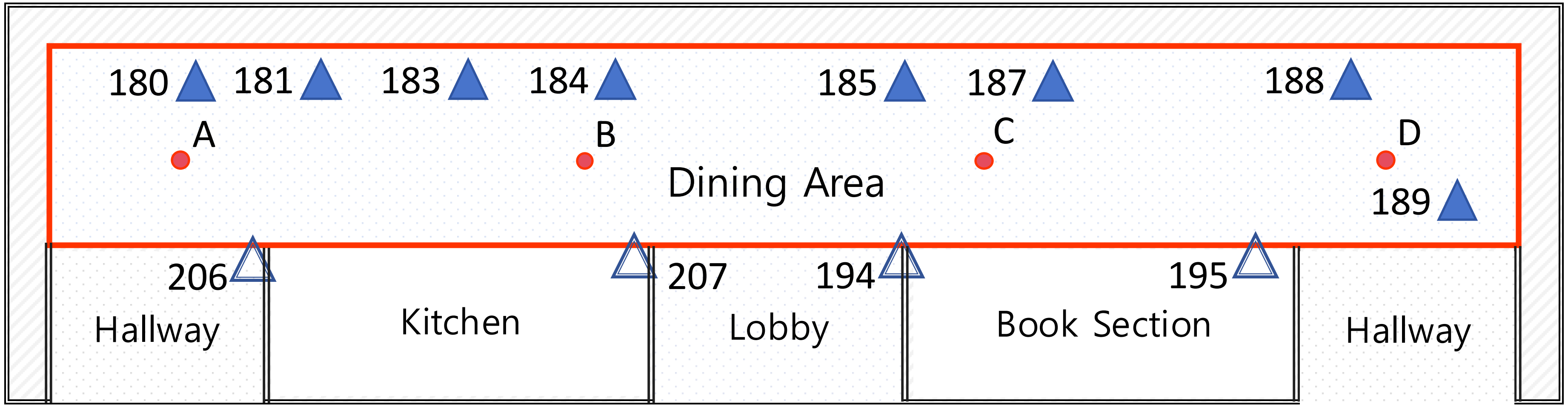


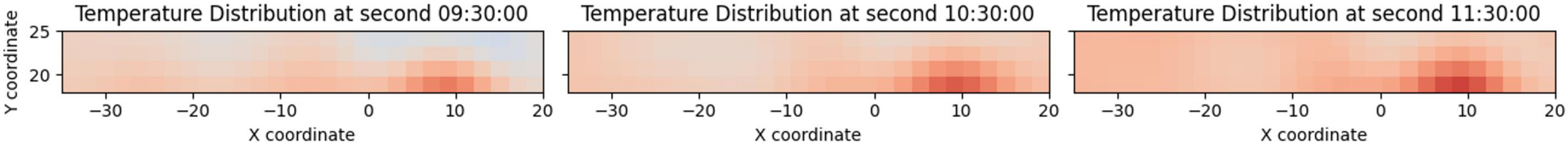
- a dining space of 56 meters by 8 meters
- 8 fixed temperature sensors placed at a height of 2.2 meters
- 4 more sensors in open areas outside the dining area

dataset collected at the Minoh Campus of Osaka University by Osaka University and Daikin Industries, Ltd on June 12th, 2024

4 Experimental Setup - Dataset

- **Real-world temperature data**

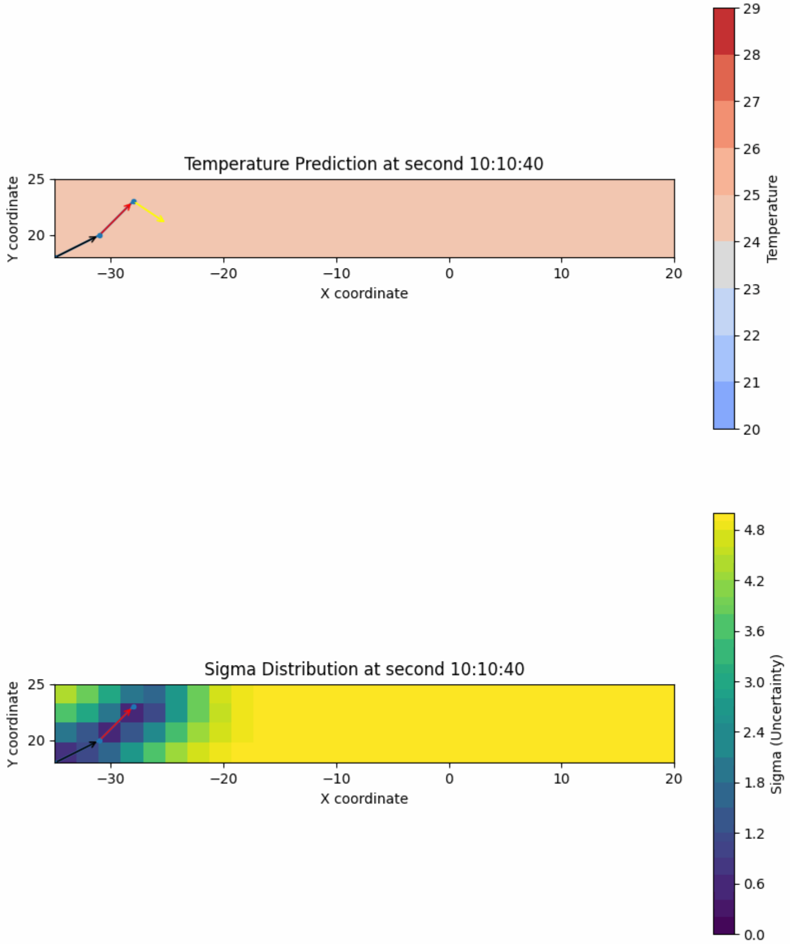




dataset collected at the Minoh Campus of Osaka University by Osaka University and Daikin Industries, Ltd on June 12th, 2024

5 Experimental Result - Monitoring Path

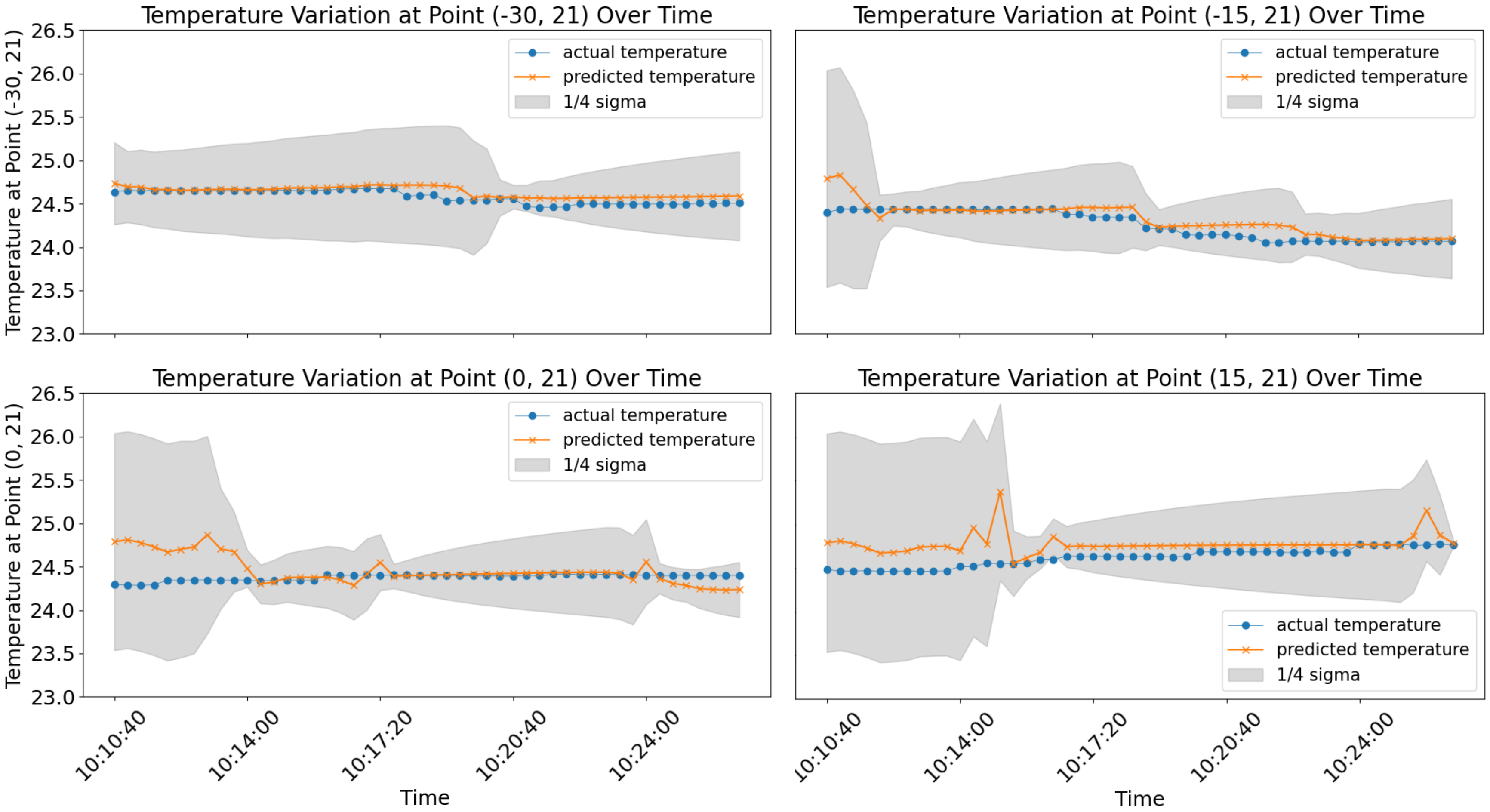
- **estimated temperature distribution and uncertainty**



- Monitoring Time: 10:10am~10:40am
- Black: most recent 20 movements
- Light-colored: predicted optimal path in next 40s
    - Red: current movement
    - Yellow: next movement

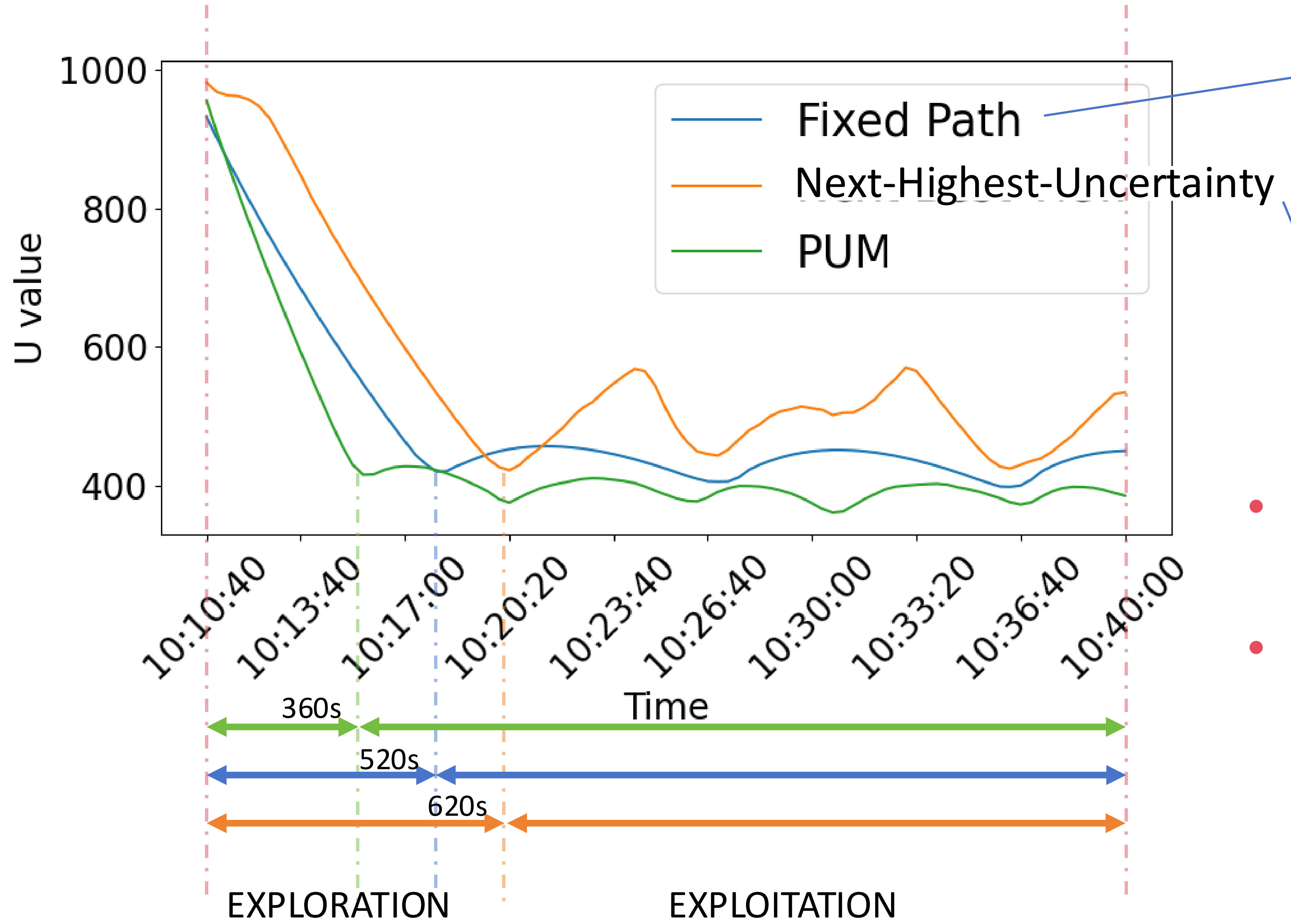
5 Experimental Result - Accuracy

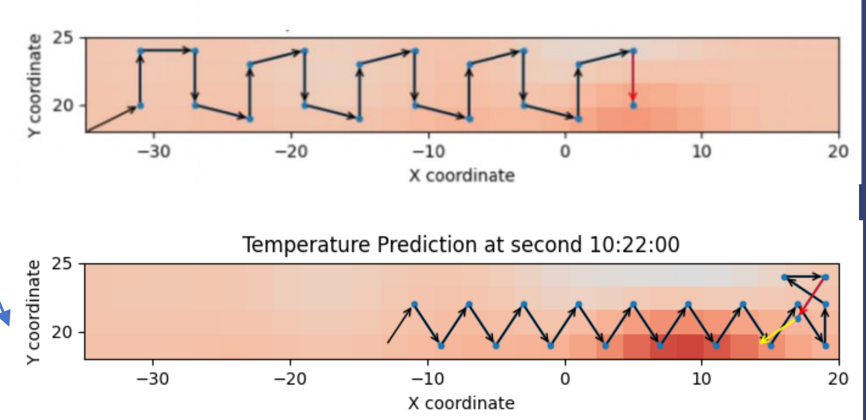
- **Temperature at 4 points**



Orange line:
predicted temperature
Blue dotted line:
actual temperature
Grey area:
1/4 sigma
(uncertainty range)

5 Experimental Result - Efficiency





- Exploration: **time savings** of 30.77% and 41.94%
- Exploitation: **global uncertainty** reduction by 7.91% and 9.25%

6 Conclusion

- **Predictive Uncertainty Minimization**
  - accuracy and efficiency
  - uncertainty-driven path planning
    - ✓ focuses only on predicting future model uncertainty
    - ✓ independent of the values of the environmental factors
    - ✓ suitable for **monitoring any environmental data**
      - Wi-Fi signal strength, gas concentrations, marine pollution, traffic flow .etc

Appendix – Spatio-Temporal GPR

- **Spatio-Temporal GPR(ST-GPR) Model**
  - Accounts for spatial and temporal correlations

$$\mathbf{x}^* = (\mathbf{z}^*, t^*)$$

$$y(\mathbf{z}^*, t^*) = \bar{\mathbf{y}} + \boxed{\Delta y(\mathbf{z}^*, t^*)} \quad \textit{where } \bar{\mathbf{y}} = \frac{\sum_{\mathbf{z}\in Z, t\in T} y(\mathbf{z}, t)}{|Z| \times |T|}$$

  - Spatio-Temporal Kernel Function

$$k_{ST}(\mathbf{x}_i, \mathbf{x}_j) = \sigma_0^2 \cdot \exp\left(-\frac{\|\mathbf{z}_i - \mathbf{z}_j\|^2}{2 \cdot \underset{\blacktriangle}{l^2_{\text{space}}}}\right) \cdot \exp\left(-\frac{|t_i - t_j|}{\underset{\blacktriangle}{l_{\text{time}}}}\right)$$

space decay rate

time decay rate

Appendix – Parameter Settings

- **Motion Parameter**
  - speed: 0.2~0.4 m/s
  - scanning interval: 20s
  - time scape (H): 40s

$$U(\mathbf{X}, \mathcal{C}) = \int_{t}^{t+H} \sum_{\mathbf{z} \in \mathbf{Z}} \sigma\left(\{\mathbf{z}, t\} | \mathbf{X}, \hat{\mathbf{X}}_{\mathcal{C}}\right) dt$$

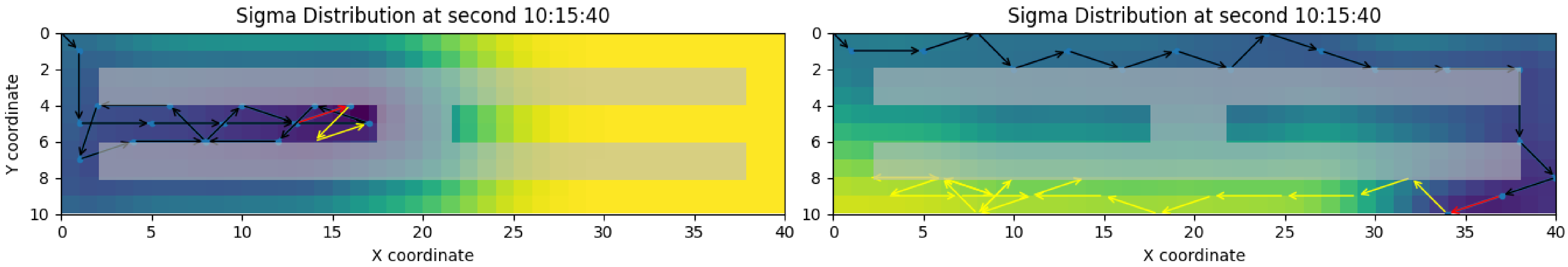
- **Spatio-Temporal Kernel Function**

$$k_{ST}\left(\mathbf{x}_i, \mathbf{x}_j\right) = \sigma_0^2 \cdot \exp\left(-\frac{\left\|\mathbf{z}_i - \mathbf{z}_j\right\|^2}{2 \cdot l_{\text{space}}^2}\right) \cdot \exp\left(-\frac{\left|t_i - t_j\right|}{l_{\text{time}}}\right)$$

$$\{l_{space}, l_{time}, \sigma_0\} = \{5, 3600, 5\}$$

Appendix – Environments with Obstacles

- **Applicability in Environments with Obstacles**



Extend the prediction horizon from 60 seconds to 400 seconds

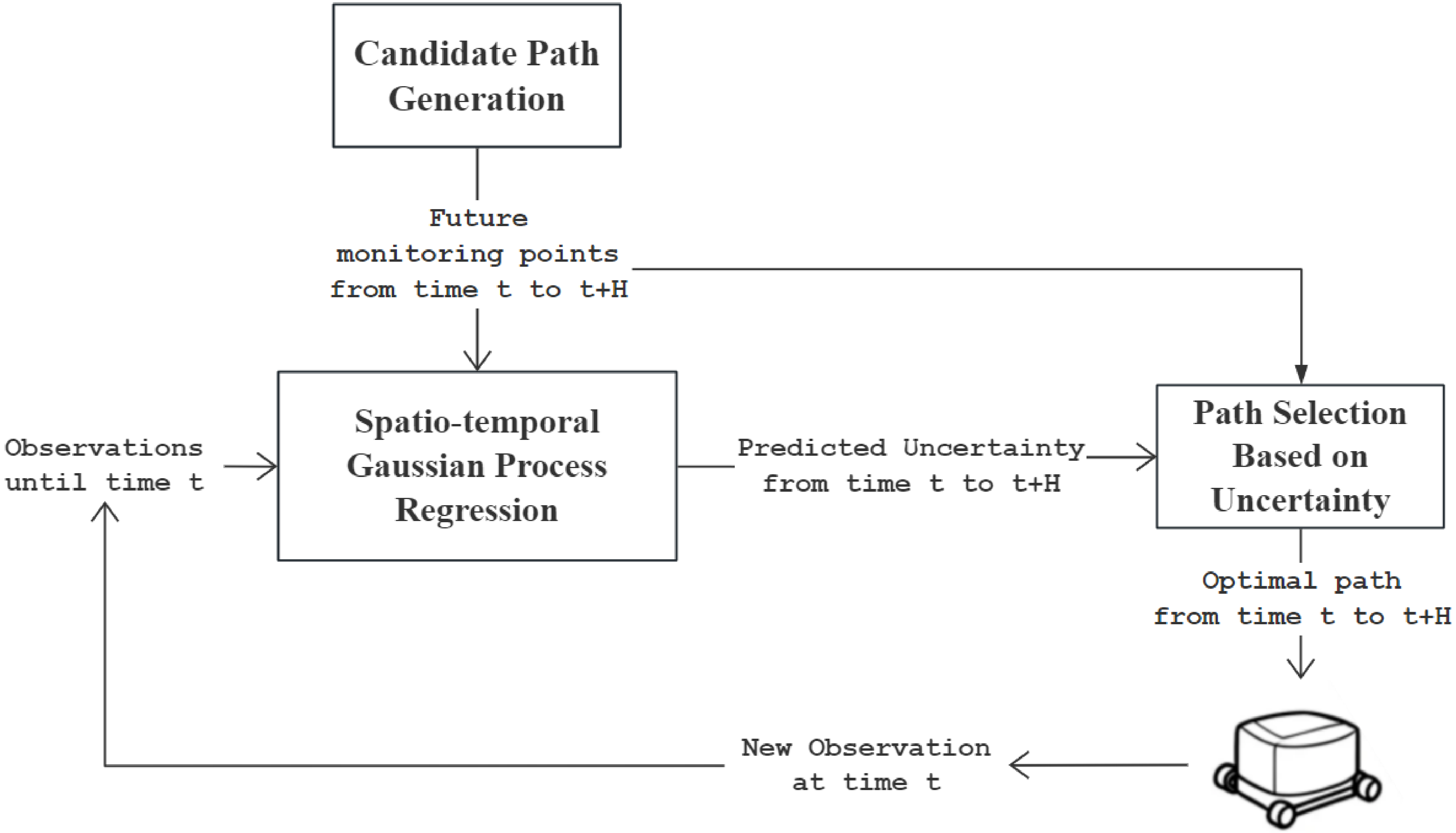
- avoid falling into local optima
- a more comprehensive analysis

Appendix – Future Work

- **Optimization of parameter values**
  - local factors such as windows and air conditioning units can lead to **asynchronous temperature changes** across different regions
  - those areas that are more susceptible to temperature changes **need to be observed more frequently** than other areas

- Automatic adjustment
  - analyze **previous predictions and observations**
  - dynamically adjust the parameters for the spatial and temporal coordinates of each point

Appendix – System Overview



Appendix – Ground Truth