

# ST-ICM: Spatial-Temporal Inference Calibration Model for Low Cost Fine-grained Mobile Sensing

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## ABSTRACT

In order to reduce the measurement error of low cost sensor in the real-time mobile sensing network, rendezvous calibration mechanism is widely used. To tackle the sparsity of reference data and the lack of calibration opportunities, we propose ST-ICM: a Spatial-Temporal Inference Calibration Model based on Gaussian Process Regression, assisting the calibration task by creating more calibration grids in both spatial and temporal dimensions. By using the GPR, the inferred grids generated by ST-ICM are associated with various confidence levels. Based on this property, we propose to make use of a hyperparameter, i.e., variance threshold, to balance the tradeoff between the quantity and quality of the inferred grids. Specifically, only the grids with variances below the threshold will be employed. We conducted experiments using a real-world dataset collected in Nanjing, China, to evaluate the performance of the proposed ST-ICM. The experimental results show that our model achieves 24% improvement on error calibration compared to the baseline.

## KEYWORDS

calibration, mobile sensing network, spatial-temporal map

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## 1 INTRODUCTION

To achieve satisfactory urban management, fine-grained sensing network (e.g., air quality sensing network) has been deployed in the city thanks to the development of IoT technology. Specifically, the deployment of LCS (low cost sensor) on vehicles can provide abundant and detailed data both spatially and temporally[4][11][8], which alleviate lack of high-resolved data due to the sparsity of standard static stations. However, the LCS in the mobile sensor network brings the inaccurate measurement problem, i.e., the LCS will show bias in monitoring over time. And these errors are not only from sensor itself but also the interference of different environments[7]. Hence, we can only mitigate these errors by periodic calibration in field.

To calibrate the LCS, many previous work adopt the rendezvous calibration mechanism. As the LCS and the reference meet within a reasonable spatial and temporal range, the LCS can utilize the reference to do calibration. However, limited number of static references usually results in the lack of calibration opportunities for rendezvous calibration. In order to solve this problem, some related work focus on how to deploy reference stations[5] or apply the multi-hop calibration[6]. Although these methods have achieved good results, they rely on the regular movement pattern of the LCS (e.g., sensor mounted on a bus). However, if we cannot obtain the trajectory regularity of a moving LCS (e.g., sensor mounted on a taxi), there is no guarantee that LCS will get sufficient or quality calibration opportunities.

Therefore, we propose ST-ICM, a Spatial-Temporal Inference Calibration Model. Instead of finding the mobility pattern, ST-ICM focuses on making better use of the reference

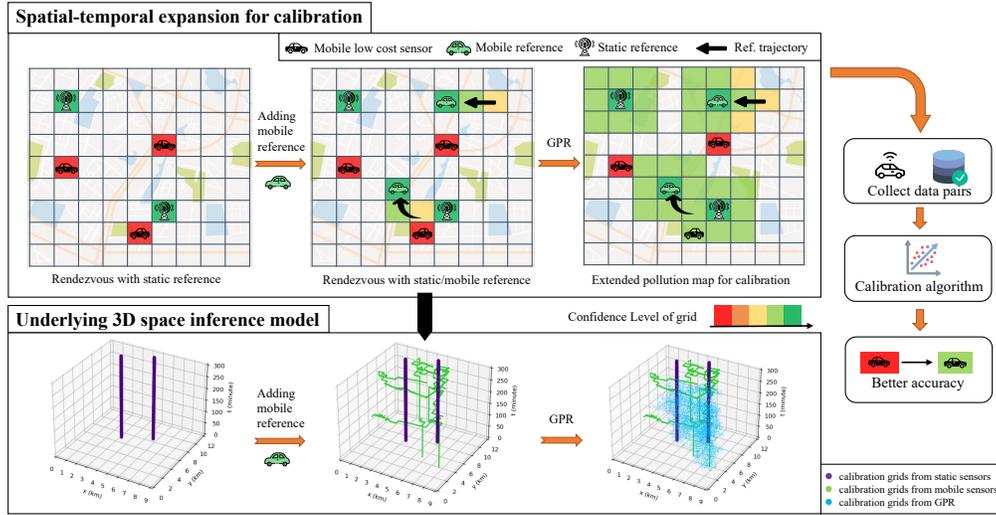


Figure 1: Overview of proposed architecture for LCS calibration

data. As shown in Fig. 1, if the spatial-temporal trajectory of a LCS meets the calibration grids, data pairs for calibration are collected. Intuitively, the more calibration grids, the more opportunities for LCS calibration. Hence, ST-ICM aims to expand the coverage of calibration grids by GPR in a spatial-temporal 3D map. Though GPR can infer all of the grids in the spatial-temporal map, not every grid generated is suitable for calibration, since they are of different confidence levels. ST-ICM measures the degrees of confidence with the variance in the GPR results. Only the grids with variances below a variance threshold will be employed. We finally find the best variance threshold to control the quantity and quality of calibration grids. Our contributions can be summarized as: 1) we propose ST-ICM that expands the total calibration grids in the spatial-temporal map, providing LCS more opportunities for rendezvous calibration; 2) for these additional calibration grids, ST-ICM measure the degree of confidence with the variance in the GPR results. We optimize our ST-ICM by evaluating the variance threshold that determines whether a spatial-temporal grid can be a calibration grid; 3) we evaluate ST-ICM on the real world dataset of PM<sub>2.5</sub> measurements. The results indicate the potential of our work.

## 2 METHODOLOGY

### 2.1 Overview

Fig. 1 shows how we utilize GPR to tackle the LCS calibration task step by step. In the leftmost picture, it is the scenario that only static reference stations exist, and it provide sparse reference data shown in the respective  $x - y - t$  3D space below the  $x - y$  2D map. Then mobile reference sensors are added to the city, covering more area with extra reference measurements, whose confidence level may decrease as time

goes. With a collection of data provided by both the static and mobile references, we use GPR to infer PM<sub>2.5</sub> concentration in larger area[2][3], and each inferred grid has a variance indicating its uncertainty, and we set a variance threshold to control the number and the quality of calibration grids.

Specifically, we first divide the entire city map into uniform  $l * l$  grids. The measurements provided by static and mobile references are denoted as  $r$ . And the grids containing  $r$  are called calibration grids  $g$ . Using the reference measurements  $r$ , we can infer extra reference measurements  $r'$  on the adjacent grids or in the adjacent time intervals at the current grid by GPR, and denote these expanded calibration grids as  $g'$ . With all calibration grids  $g$  and  $g'$ , the LCS can collect data pairs  $(u, r)$  or  $(u, r')$  at a time point  $t$  for each calibration grid it enters, where  $u$  is the uncalibrated measurement of LCS. When the LCS collects  $n$  data pairs, the calibration function  $C(u)$  can be computed by least squares method to update the calibration parameters  $\theta$  of the LCS.

### 2.2 GPR Inference Model

Given a training set  $T = \{(z^i, r^i)\}_{i=1}^N$ , consisting of i.i.d. (independent and identically distributed) samples from some unknown distribution, the GPR model can be defined as:  $r^i = p(z^i) + \epsilon$ ,  $i = 1, \dots, N$ . And  $z$  is the data tuple  $(x, y, t)$  where  $x$  is the latitude,  $y$  is the longitude and  $t$  is the timestamp of the tuple.  $\epsilon$  is i.i.d. noise subjected to normal distribution  $N(0, \sigma^2)$ .

After the GPR model is defined, given a collection of test samples  $V = \{(z_*, r_*)\}_{i=1}^{N_*}$ , derived from the same undiscovered distribution as training set  $T$ , the posterior distribution  $(r_* | r, z, z_*)$  complies to  $N(\mu_*, \sigma_*)$  according to conditional Gaussian's properties, where  $\mu_*$  referring to the inference of PM<sub>2.5</sub> value, and  $\sigma_*$  is the variance indicating the uncertainty

of the inference[9]. Specifically, we set a variance threshold as a hyperparameter which determines whether an inferred grid is the calibration grid. When we set it low, meaning the calibration grids have lower uncertainty, resulting in fewer calibration grids. In this case, each calibration grid may be very accurate, but the calibration opportunities decrease. When we set it high, the calibration grids in space and time will increase, and the calibration opportunities of LCSs will boost, but the calibration performance may decline since the references are of high uncertainty. Therefore, finding an appropriate variance threshold is crucial in optimizing our model. And we evaluate this hyperparameter in next section.

### 3 EXPERIMENTAL EVALUATION

#### 3.1 Experimental setup

Our experiments are conducted in Qinhuai District, Nanjing. We deployed 21 static monitoring stations and dispatched 22 vehicles (including buses and taxis) carrying sensors to detect PM2.5 concentration values. The experiment lasted from November 28 to December 6, 2021, covering a total of 127.5 square kilometers of the urban area. To verify the performance of our experiments, we take the data of 21 static monitoring stations as the reference static sensors. Among the 22 mobile LCSs, 4 are assumed as reference mobile sensors, and the other 18 are the LCSs needed to be calibrated, on which we manually add a time-varying linear noise. We take the original measurements as groundtruth. The spatial-temporal grid size is set as 500m\*500m\*1min, meaning the GPR will be implemented every minute to update the inferred values with variances of all grids, ensuring that the data for calibration is as accurate as possible. This setting basically meets our requirements for fine-grained urban sensing. MAE (Mean Absolute Error) is used as the evaluation metric.

**Table 1: The Calibration MAE of Our Model**

	MAE of Calibration Data
No Calibration	5.71
Simple Calibration	2.81
<b>ST-ICM</b>	<b>2.14</b>

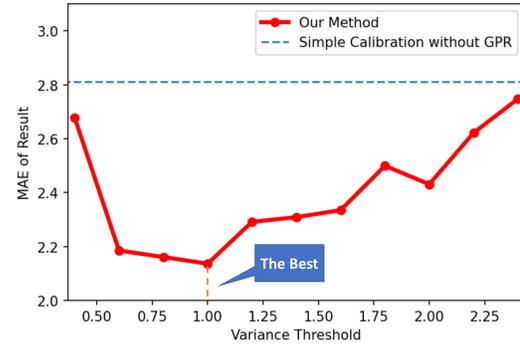
#### 3.2 Evaluation of ST-ICM

We use two baselines for comparison with our method. "No Calibration" refers to the data errors without calibration at all. "Simple Calibration" refers to the calibration data without using GPR. In this case, our calibration grids will be relatively sparse, and many LCSs cannot be calibrated in time, thus accumulating errors. Table 1 shows the performance of our method. Our method improves 24% compared with the baseline "Simple Calibration" without GPR.

#### 3.3 Evaluation of ST-ICM under different variance threshold

Fig. 2 shows the ST-ICM performance under different threshold settings. When we take a variance threshold of 1, we

get the best balance between the quantity and quality of calibration grids and achieve the best model performance.



**Figure 2: Results of Different Variance Threshold**

### 4 CONCLUSION AND OUTLOOK

In this paper, we propose a model leveraging inference techniques for LCS calibration, and provide a new perspective to consider calibration in a spatial-temporal map. In the future, we plan to investigate other trade offs in our model (e.g., the grid size), and the dispatch algorithms[1][10] for the mobile references to achieve better inference for calibration.

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