Poster:Spatio-Temporal Aware Collaborative Mobile Sensing with Online Multi-Hop Calibration

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ABSTRACT

Real-time accurate air quality data is very important for pollution exposure monitoring and urban planning. However, there are limited high-quality air quality monitoring stations (AQMS) in cities due to their high equipment costs. To provide real-time and accurate data covering large area, this paper proposes a novel scheme that jointly considers online multi-hop calibration and spatio-temporal coverage in route selection for mobile sensors. A novel sensor carrier selection problem (SCSP) is formulated, which aims to maximize the spatio-temporal coverage ratio and guarantee the accuracy of measurements through sensor calibration. An online Bayesian based collaborative calibration (OBCC) scheme is proposed to relax the multi-hop calibration constraint in the SCSP. Based on the OBCC, a multi-hop calibration judgment algorithm (MCJA) is proposed to decide whether the data accuracy of a given set of routes can be guaranteed through collaborative calibration. Furthermore, a heuristic sensor route selection algorithm (SRSA) is then developed to solve the SCSP.

CCS CONCEPTS

• **Computing methodologies** → Supervised learning; Kernel methods; Learning linear models; Modeling methodologies; • **Mathematics of computing** → Time series analysis;

KEYWORDS

collaborative mobile sensing, Bayesian estimation, multi-hop calibration, spatio-temporal coverage

1 INTRODUCTION

Air pollution is one of the most important environmental problems and has attracted enormous attention in recent years [2]. However, there are insufficient air quality monitoring stations (AQMS) in cities due to the expensive cost for building and maintaining them. For example, a typical AQMS costs about 200,000 USD for deployment and 30,000 USD per year for maintenance [5]. In recent years, low-cost sensors (≈100 USD) have been used to assist AQMS for monitoring urban area. Although low-cost sensors are generally calibrated before deployment, they suffer from noise and drift over time [1]. Thus, low-cost sensors require frequent re-calibration (e.g. with AQMS) to maintain data accuracy.

Installing low-cost sensors on buses becomes a cost-effective solution for air quality monitoring. The sensors on buses can be re-calibrated from time to time when meeting with the AQMS. Nevertheless, there are few bus routes that can pass by the AQMS frequently for direct (or one-hop) calibration. Fortunately, after calibrating with the AQMS, the one-hop calibrated sensors can learn the calibration curve [4] and can provide accurate measurements for calibrating other sensors. Even though some bus routes can not meet frequently with the AQMS, they may meet frequently with some one-hop calibrated sensors. The sensors on these bus routes can then be calibrated through two-hop calibration. Similarly, this process can be repeated as three-hop calibration, four-hop calibration, and so on.

Mounting low-cost sensors on buses faces two major challenges, including real-time accurate measurements and spatio-temporal coverage. Real-time Air Quality Index (AQI) map is very popular and many state-owned projects make their measurements open to the public by publishing real-time data online [3]. Traditional off-line calibration requires a large amount of training data to learn the calibration curve and thus can not provide real-time accurate measurements. In addition, the spatio-temporal coverage has to be jointly considered in bus route selection to provide sufficient data accuracy and coverage. Each mobile sensor requires frequent calibration, either directly with the AQMS or indirectly through multi-hop calibration.

To tackle the above challenges, we propose a generic model for collaborative mobile sensing considering both spatio-temporal coverage and data accuracy.

2 SYSTEM MODEL AND PROBLEM FORMULATION

We consider a scenario where there are a set of M mobile sensors, $\mathcal{M} \triangleq \{m|m_1, m_2, \ldots, m_M\}$, mounted on public transportation such as buses. Let $\mathcal{R}$ be the set of routes of public transportation. In the temporal domain we divide the time, $\mathcal{T} \triangleq \{t|t_1, t_2, \ldots, t_T\}$, into T

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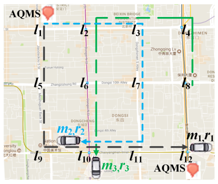

Figure 1: Multi-hop calibration scenario.

time slots with the same interval. In the spatial domain, we divide the whole urban area, $\mathcal{L} \triangleq \{l | l_1, l_2, \ldots, l_L\}$, into L grid cells with the same size. Let $\mathcal{L}^*$ be the set of grid cells containing AQMS, $\mathcal{L}^* \subset \mathcal{L}$.

Let $\mathcal{A} \triangleq \{a | a_1, a_2, \ldots, a_k\}$ be the set of k different types of air quality data such as PM_{10}, $PM_{2.5}$, NO_2, and O_3.Let $\hat{x}^a_l(t)$ be the estimation of true value of a in grid cell l at time t.

Figure 1 illustrates a simple scenario of multi-hop calibration, where $\mathbf{t} = \{t_1, t_2, t_3, t_4, t_5, t_6\}$, $\mathcal{L}^* = \{l_1, l_{12}\}$ and there are three mobile sensors m_1, m_2, and m_3 moving in the region. Three dotted lines with different colors represent three different routes r_1, r_2, and r_3. Suppose that all mobile sensors can measure the same type of air quality information a, where $a \in \mathcal{A}$.

To simplify the scenario, each mobile sensor only has to meet with the AQMS or any other calibrated mobile sensors two times along their routes. As shown in Figure 1, m_1 meets with the AQMS in l_1 and l_{12} at t_1 and t_6. Thus, the measurements from m_1 can be calibrated and m_1 is an on-hop calibration sensor. Similarly, m_2 meets with the AQMS in l_1 at t_1 and arrives l_{11} at t_5. Although m_2 meets with the AQMS only once, we can obtain $\hat{x}^a_{l_{11}}(t_5)$ from m_1. Thus, the measurements from m_2 can be calibrated in two hop calibration. Similarly, m_3 does not meet directly with any AQMS, but it meets with m_2 at t_3 and t_6. Since we can obtain $\hat{x}^a_{l_3}(t_3)$ and $\hat{x}^a_{l_{10}}(t_6)$ from m_2, the measurements from m_3 can also be calibrated through three hop calibration.

Given a set of routes from the public transportation (e.g. city buses) $\mathcal{R}$ and a set of mobile sensors $\mathcal{M}$, the formal goal of the sensor carrier selection problem (SCSP) is to select a subset of routes for $\mathcal{M}$, $R(\mathcal{M})$, so that the spatio-temporal cover ratio during $\mathbf{t}$ under resolution Δt is maximized, while the sensor calibration opportunities are guaranteed.

3 PROPOSED SOLUTIONS

To solve the SCSP, we first propose an online Bayesian based collaborative calibration (OBCC) method, which leverages the historical calibration curve of mobile sensors to improve data accuracy. The OBCC can relax the multi-hop calibration constraint in the SCSP by reducing meeting times with the AQMS or any other calibrated mobile sensors. Then, based on the OBCC, we propose a heuristic algorithm to solve the SCSP, which supports collaborative multi-hop calibration between the mobile sensors and the AQMS. Furthermore, based on the OBCC, a multi-hop calibration judgment algorithm (MCJA) is proposed to decide whether the data accuracy of a given set of routes can be guaranteed through collaborative calibration. Finally, based on the result of the MCJA, a heuristic sensor route selection algorithm (SRSA) is proposed to solve the SCSP, which supports collaborative multi-hop calibration between the mobile sensors and the AQMS. It is well known that, a simple greedy algorithm can obtain a bound of $(1 - e^{-1})$ for the maximum coverage problem (MCP). However, with the muti-hop calibration constraint, the SCSP is much more complicated than the MCP. Due to the strong constraint, greedy algorithm may not find any feasible solutions.

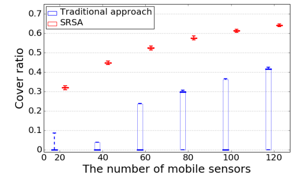

Figure 2: Comparison with traditional approach on different number of mobile sensors.

4 SIMULATION RESULTS

We compare our approach with the traditional approach varying the number of mobile sensors. As shown in Figure 2, the SRSA performs much better than the traditional approach in all number of mobile sensors. As the number of mobile sensors increases from 20 to 40 and 60, the spatio-temporal cover ratio by the SRSA increases from 32% to 44.8% and 52.4%. As the number of mobile sensors increases from 80 and 100, it increases 25% of the mobile sensors but results in only 3.6% increase in the spatio-temporal coverage ratio (from 57.6% to 61.2%). Thus, there is a trade off between the number of mobile sensors in use and the spatio-temporal coverage ratio.

5 CONCLUSIONS

In this paper, we proposed a generic model for mobile sensors to monitor urban environment considering collaborative multi-hop calibration. Our model jointly considers spatio-temporal coverage and sensor calibration in route selection for the mobile sensors. We formulated a novel sensor carrier selection problem (SCSP), which can guarantee data accuracy by sensor calibration and maximize the temporal-spatial coverage at the same time. Firstly, we proposed the OBCC to relax the multi-hop calibration constraint in the SCSP. Then, based on the OBCC, we propose the MCJA to measure whether we can guarantee the data accuracy through the OBCC. Finally, based on the MCJA, we further developed the SRSA to solve the SCSP. Simulation results showed that our proposed algorithm can reduce up to 60% of the total mobile sensors in use and obtain higher spatio-temporal coverage.

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