Logistics of Urban Monitoring with Moving Sensors

Amir Ahmadian[a], Mehdi Nourinejad[b], and Matthew Roorda[a]

a Department of Civil and Mineral Engineering, University of Toronto
b Department of Civil Engineering, York University

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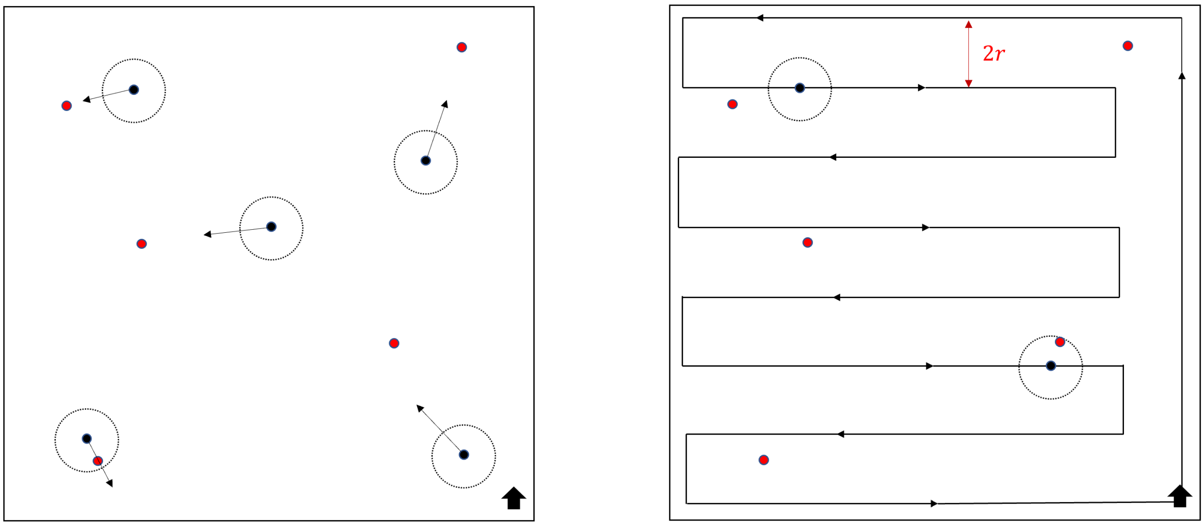
1 Introduction

Advanced sensor technologies and communication systems allow real-time monitoring of infrastructure such as roads, parking lots, and transit stops. Infrastructure monitoring aids in collecting congestion information, identifying potential anomalies or incidents, and providing information to relevant stakeholders like road users or parking seekers. Despite their advantages, comprehensive and timely monitoring across vast and often inaccessible areas remains a significant challenge. Traditional monitoring methods, including manual inspections and stationary cameras, fail to achieve the desired coverage and response time. This limitation underscores the need for innovative solutions that can enhance the reach and quality of monitoring systems.

The use of mobile sensors deployed on crowd-sourced carriers (e.g., buses, drones, or bikes) is a new alternative to stationary sensors placed at one location. Owing to their high mobility, these carriers enable the sensors to survey the surrounding areas extensively. Factors that affect the data collection process are the carrier type, reliable schedules, and predictable trajectories (Ji *et al.*, 2023). However, while there is a growing body of work focused on the technological and operational aspects of such sensors (Ahnn & Potkonjak, 2013, Skordylis & Trigoni, 2011), as well as their data management and analysis capabilities (Alessandroni *et al.*, 2015, Turcanu *et al.*, 2016), there remains a gap in characterizing and optimizing the logistics of mobile sensors such as identifying the fleet size, sensor range, and monitoring strategy to ensure consistent and comprehensive coverage. Furthermore, in one study, O'Keeffe *et al.* (2019) has explored the efficacy of using a limited number of vehicles for city-wide monitoring; however, did not explore the frequency and reliability of coverage required to meet the needs of various operational standards.

This study proposes a systematic approach to optimize the fleet size of crowd-sourced vehicles and the range of their sensors. We aim to reach the desired ratio of events occurring within a given monitoring area to achieve a coverage goal. The study will define a base problem and explore two scenarios: one to identify the upper bounds and another to determine the lower bounds of fleet size and sensor range required to achieve the desired level of coverage.

This study provides a strategic framework for enhancing the efficiency and coverage of mobile sensor networks in urban monitoring. By optimizing the deployment of crowd-sourced vehicles and their sensor capabilities, we address critical challenges in achieving extensive and reliable data collection across urban landscapes.



(a) (b)

Figure 1 – *(a). Schematic of the base problem. Red dots indicate the desired points to be sensed, black dots indicate the sensing vehicles, and the dashed circles are their corresponding sensing range. (b). Schematic of the upper bound problem and the path* $\mathscr{P}$*, which traverses the region* $\mathscr{R}$ *horizontally a total of* $2m = 8$ *times.*

2 Methodology

Consider a plane $\mathscr{R}$ with an area of A, and a fleet of sensor-equipped carriers (e.g., drones) tasked to survey the area and collect information on a phenomenon of interest such as traffic congestion. We assume the sensing vehicles' speed is consistent throughout the survey process without any drastic changes. Each sensing vehicle, constrained by the detection range of its on-board sensor, can monitor an area within a radius$r$ from its location.

We present the cost of adding one carrier to the fleet of sensors as c_n. Furthermore, the acquisition and maintenance cost of sensors (e.g. LiDARs, specialized detection cameras) increases with range, given the additional and higher-resolution laser projectors required. We assume here that the overall amortized cost of each sensor increases exponentially with its range at a marginal cost of c_r. Therefore, the total cost of operating the mobile sensing system is

$$C(n, r) = n(c_n + c_r e^{kr}) \tag{1}$$

where n is the number of sensors in the fleet, or in other words the fleet size, r is the range of the on-board sensors, and k is the parameter of the cost function.

2.1 Base Problem

In the base problem, we assume sensing vehicles are randomly distributed in $\mathscr{R}$ and travel at a constant speed (V). Once an event is spawned on the plane, the closest sensor moves toward it for the purpose of observing it. A schematic of the base problem is provided in Figure 1(a).

Events occur in $\mathscr{R}$ according to a Poisson process with rate λ and are uniformly distributed over space. Each event has a duration time (t_d) that follows a negative exponential distribution with a mean of μ. Once the duration time has elapsed, the event expires (e.g., the illegal parker leaves) and can no longer be observed. The objective is to ensure that at least α percentage of the events are detected before they expire. To achieve this, we seek to minimize the total cost of the sensing fleet by determining the optimal number of vehicles (n) and their sensing range (r), while satisfying the desired coverage requirements.

By formulating this problem as an optimization model, we have

$$\min_{n,r} \quad C(n,r) \tag{2}$$

$$\text{s.t.} \quad \rho \geq \alpha. \tag{3}$$

where ρ is the expected coverage ratio and α is the minimum desired coverage.

The problem above is a non-linear problem, and obtaining a closed-form solution for it in its base format is infeasible. Therefore, we aim to perform an asymptotic analysis to determine an upper and lower bound for minimizing sensing costs while ensuring adequate coverage.

3 Results

3.1 Analysis of the Upper Bound

In this section, we aim to find an upper bound solution for the optimization problem introduced above and perform numerical analyses of the optimal fleet size and range. Let m be an integer, and consider the path $\mathscr{P}$ obtained by traversing the width of $\mathscr{R}$ horizontally a total of $2m$ times, starting at the point horizontally and vertically r away from the upper rightmost corner of $\mathscr{R}$ and moving downward by an amount $2r$. Note that the sensors' movement along $\mathscr{P}$ is unidirectional, as shown in Figure 1(b). It is obvious that the length of $\mathscr{P}$ is simply

$$L = 4(l - 2r) + (2m - 2)(l - 4r) \tag{4}$$

where l is the length of side of $\mathscr{R}$. In the optimal path, m is equal to $\frac{l}{4r}$, and traversing along the optimal path allows the sensors the capability to cover every part of the $\mathscr{R}$ within their ranges without any overlaps. There is the possibility of l not being perfectly divisible by $2r$ and more accurately, $\lceil \frac{l}{4r} \rceil$ must be used. However, since we are investigating the upper bound problem, for the cases that $\frac{l}{4r}$ is not an integer, we will expand $\mathscr{R}$ until we reach a new l perfectly divisible by $4r$. By replacing m in Equation (4) we have

$$L = \frac{l^2}{2r}. \tag{5}$$

Sensing vehicles are assumed to be uniformly distributed along this path, so the headway between every two consecutive sensing vehicles is equal to $\frac{L}{n}$. To calculate the expected coverage ratio, ρ, we need to find the probability of events being covered. Since the probability of an event being covered is different based on the events' spawning location, the coverage statement needs to be broken into two parts. If an event occurs inside the range of any of the sensors, it is observed with a probability of 1, and if it occurs outside of them, it will be observed by the next sensor coming toward it unless the time that sensor needs to reach an observable distance away from that event exceeds the event's duration (t_d). Rewriting in mathematical terms we have

$$\rho = \frac{2rn}{L} \times 1 + n \times (1 - \frac{2rn}{L}) \times \frac{1}{L - 2rn} \times \int_0^{\frac{L-2rn}{n}} P(\frac{x}{V} \leq t_d) dx, \tag{6}$$

where x is the sensor's location on the path when for the first time observes the event and we integrate over x to have considered all of the path. Since $P(\frac{x}{V} \leq t_d)$ follows a negative exponential distribution with mean value of μ, we have

$$\rho = \frac{2rn}{L} + \frac{n}{L} \int_0^{\frac{L-2rn}{n}} e^{\frac{-x}{\mu V}} dx = \rho = \frac{2rn}{L} + \frac{n}{L}(\mu V(1 - e^{\frac{1}{\mu V}(2r - \frac{L}{n})})). \tag{7}$$

Interestingly the coverage ratio is independent of the occurrence rate of the events (λ). Furthermore, the first component of the expression, $\frac{2rn}{L}$, is equal to the coverage achieved with static sensors; therefore, the second component highlights the additional coverage gained through the mobility of the sensors.

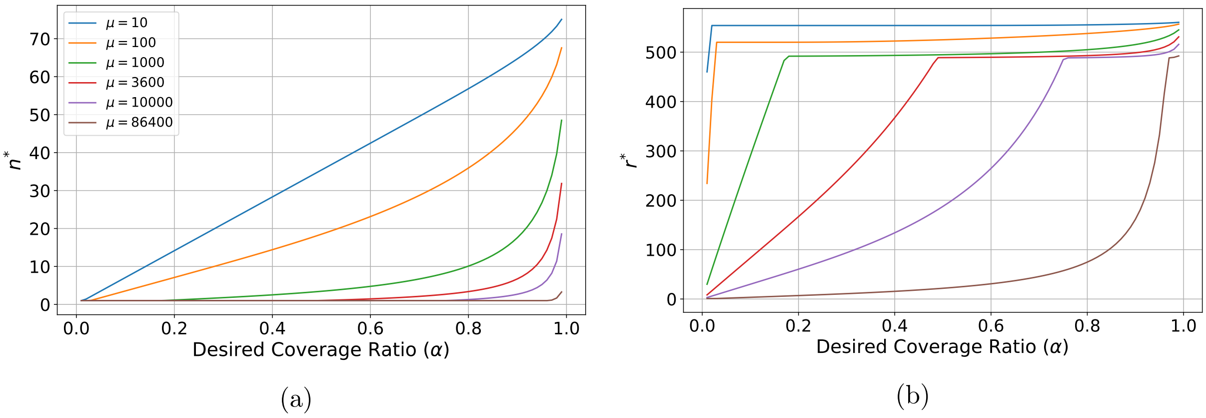


Figure 2 – *(a) Optimal number of sensing vehicles, n, and (b) optimal sensor range, $r(meters)$, for various desired coverage ratios, α, and various mean duration time of events, $\mu(seconds)$. (Parameters: $V = 60(\frac{Km}{hour})$, $l = 10(Km)$, $c_r = 10$, $c_n = 5000$, and $k = 0.01$)*

3.2 Numerical Analysis

We conducted numerical analyses for the upper bound problem, and Figure 2 illustrates the results. From the optimal plots, we observe distinct trends based on the events' mean expiration time, μ. For low μ values (e.g., 10 seconds), the sensor range quickly asymptotes to an optimal value, making the increase in the number of sensors, n, the primary contributor to achieving the additional coverage required as α rises. In contrast, at high μ values (e.g., one day), the optimal values of n and r increase at a slow rate. However, as α reaches very high values, both n and r experience a steep rise to ensure adequate coverage, though r still asymptotes to an optimal value.

With the numerical results for the upper bound established, the next steps in this study are to identify the lower bound solution and derive closed-form expressions for the optimal number of sensing vehicles and sensor range in both upper and lower bound cases. Additionally, we aim to investigate the sensitivity of the optimal values to variations in key parameters, such as α and μ, to understand how changes in the desired coverage ratio or event's duration impact the overall effectiveness of the system. This sensitivity analysis could reveal critical thresholds and inform strategies for adaptive sensor deployment based on specific environmental or operational constraints.

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