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OPTIMIZING URBAN MONITORING BETWEEN STATIONARY, OPPORTUNISTIC VEHICULAR, AND HYBRID SENSING

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ABSTRACT:

Urban monitoring based on wireless sensor networks is a recent paradigm that exploits a large number of low-cost sensors deployed in certain places or/and on mobile devices to collect data ubiquitously at a large scale. In this study, we explore and compare the coverage of *stationary* and *opportunistic vehicular* sensing methods with respect to the requirements of a task at hand. We distinguish spatial granularity, temporal granularity, and budget constraints. First we compare the spatio-temporal coverage of stationary sensing and opportunistic vehicular sensing for various tasks, which demonstrates that these two sensing methods are suitable for different tasks. Then we propose a *hybrid* sensing deployment framework integrating a genetic algorithm to achieve the maximum spatio-temporal coverage for specific tasks. Experiments with a real-world vehicle trajectory dataset demonstrate that the proposed hybrid sensing framework achieves the maximum spatio-temporal coverage in various tasks. Our results provide fundamental guidelines on network planning for urban monitoring applications.

1. INTRODUCTION

Over the past decades, with the advance in the technology of low-cost sensors and wireless communication, wireless sensor networks (WSNs) have evolved to a new data collection paradigm for urban monitoring at a large scale (Zhao and Guibas, 2004, Duckham, 2013). The new paradigm plays a significant role in smart city domain by empowering city computing for decision makers (Anjomshoaa et al., 2018, Lee et al., 2020). Compared with traditional stationary environmental monitoring stations, the low-cost sensors can be deployed in larger numbers at finer spatial granularity (Mao et al., 2012). WSNs have been applied for example in weather monitoring in the wild (Barrenetxea et al., 2008), and air pollution monitoring in urban environments (Boubrima, 2019, Mao et al., 2012).

Low-cost sensors can be deployed in *stationary sensing* (SS) to collect data at selected locations over long periods of time, thus, with static and limited spatial coverage (O'Keeffe et al., 2019, Anjomshoaa et al., 2021). Alternatively, those sensors can also be mounted on mobile devices, e.g., smartphones (Ji et al., 2016), drones (Yanmaz et al., 2018), and vehicles (Apte et al., 2017, Lee and Gerla, 2010), or be directly carried by humans (Ma et al., 2020). Mobile sensors are able to monitor certain phenomena in places traversed by their hosts, i.e., at varying locations. In *opportunistic vehicular sensing* (OVS), a common kind of mobile sensing, mobile sensors are deployed on a set of existing vehicles without any influence on the routes of these vehicles (Anjomshoaa et al., 2021). Thus, OVS improves the spatial coverage compared to SS, but at the cost of temporal coverage (Boubrima, 2019).

The concept of coverage is a fundamental metric to evaluate the sensing quality (Chen et al., 2017, Ghosh and Das, 2008, Zhao et al., 2015), and it includes both the spatial and temporal domains. SS and OVS each have their merits and drawbacks in their spatial and temporal coverage. Several studies revealed already the benefits of OVS in the sensing coverage over SS, but only at a given spatio-temporal granularity depending on phenomena being monitored in those studies (Chen et al., 2017, Gao et al., 2016, O'Keeffe et al., 2019). However, the required spatio-temporal granularity varies with the properties of phenomena being monitored and the applications in mind. For instance, a high spatial density is needed for monitoring noise, whereas temperature can be captured with lower spatial granularity (Anjomshoaa et al., 2021). In the temporal domain, monitoring street surface quality is less sensitive to temporal granularity compared to monitoring traffic flow. Besides, task initiators allocate budgets to the sensing, reflecting the value of the generated information. These budgets determine how many sensors can be deployed for sensing tasks, creating an optimization problem for the coverage (Asprone et al., 2021): Given the requirements of a certain task, in terms of *spatial* granularity, *temporal* granularity, and *budget* limitations, the task is to determine which sensing method is superior to the other and should be chosen by an agency.

To the best of our knowledge, this issue has not been addressed in the literature. To fill the gap, this paper addresses a number of research questions. The initial one is: *For which tasks does the spatio-temporal coverage of one sensing method exceed the other?* To answer the question, we estimate and compare the spatio-temporal coverage of SS and OVS for tasks with various requirements. The next research questions address the optimal deployment of a limited number of sensors to achieve a high spatio-temporal coverage, which has been a key problem in urban monitoring. Existing studies mainly focus either on SS (Mao et al., 2012, Chakrabarty et al., 2002) or vehicular sensing (He et al., 2015, Asprone et al., 2021, Zhao et al., 2015, Cortes et al., 2004) to achieve maximum coverage. Although several studies have discussed *hybrid sensing* (HS), consisting of stationary and mobile sensors, these studies aim at optimizing vehicle selection or moving route planning based

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on the known number and placements of stationary sensors to obtain a coverage (Zhang and Fok, 2017, Zygowski and Jaekel, 2018). To the best of our knowledge, no study explores how to co-deploy stationary sensors in HS. The challenge in co-deployment is to achieve the optimal spatio-temporal coverage for a limited number of sensors with an appropriate split between stationary and mobile sensors. The research questions that need to be addressed include *a) can HS achieve higher spatio-temporal coverage than SS and OVS for a given task? b) what is the optimal configuration of SS and OVS in hybrid sensing?* To answer these questions, we propose a HS framework that optimizes the deployment of HS to achieve an expected optimal spatio-temporal coverage according to historical trajectories of candidate vehicles and task requirements.

The main contributions of this study can be summarized as follows:

- We demonstrate that SS can achieve a higher spatio-temporal coverage over OVS for some tasks, and vice versa.
- We propose a HS framework integrating an objective function, a genetic algorithm, and a stationary sensor deployment mechanism to optimize HS for urban monitoring with the maximum spatio-temporal coverage. The framework solves an NP-hard problem heuristically, resulting in the solution with a high sensing coverage.
- We evaluate SS, OVS, and HS on a substantial trajectory dataset from a global city, and use the case study also to verify the reliability and validity of our proposed HS framework.

Accordingly, this paper is organized as follows. In Section 2, the definition of spatio-temporal coverage and the proposed hybrid sensing method are introduced. In Section 3, we evaluate the different sensing methods and present the computational results obtained by applying the methods in real scenarios. The major conclusions and research limitations are presented in Section 4.

2. METHODOLOGY

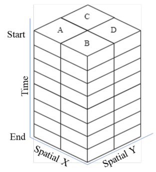
In this section, first, we present the formal definition of terms regarding the sensing task and spatio-temporal coverage (Section 2.1). Then, a framework for HS deployment is developed to obtain the maximum spatio-temporal coverage (Section 2.2).

2.1 Definitions

In this section, we give definitions regarding the sensing task and spatio-temporal coverage of sensing.

A sensing task usually has its certain task requirements and budget limitations. The task – i.e., the nature of the phenomenon being monitored and the application in mind – determines the required *spatio-temporal granularity*. The budget limitations restrict *the number of sensors* – stationary sensors as well as vehicular sensors. Therefore, a *task* is defined as monitoring a phenomenon in a target area S over a certain sensing cycle T by either SS, or OVS, or both.

Definition 1: Spatio-temporal granularity. According to the requirements of the task at hand, the target area can be divided into unit cells, where the required spatial granularity (G_s) determines the cell base, and the cell height is determined by the required temporal granularity (G_t). The task requires the coverage of each unit cell by at least one sensor. For instance, in Figure 1(a) the target area is spatially partitioned into four cells, denoted as $S = \{A, B, C, D\}$), and the time axis is divided into eight unit intervals, denoted as $T = \{t_1, ...t_8\}$. We say, G_s is 2×2 (Ji et al., 2016, Wu et al., 2019), G_t is $T/8$, and the total number of cells is 32.



(a) Target area

(b) Vehicle trajectory matrix (M_v)								
$v_i \backslash t_j$	t_1	t_2	t_3	t_4	t_5	t_6	t_7	t_8
v_1	AB	BD	D	ACD	BD	ABD	D	A
v_2	AC	C	AC	ACD	C	CD	ABD	/
v_3	/	ACD	AC	/	A	AB	A	BD

(c) $R_{SC}(j)$ of opportunistic vehicular sensing									R_{STC}
$v_i \backslash t_j$	t_1	t_2	t_3	t_4	t_5	t_6	t_7	t_8	
$v_1 v_2$	0.75	0.75	0.75	0.75	0.75	1	0.75	0.25	0.719
$v_2 v_3$	0.5	0.75	0.5	0.75	0.5	1	0.75	0.5	0.666
$v_1 v_3$	0.5	1	0.75	0.75	0.75	0.75	0.5	0.75	0.719

(d) $R_{SC}(j)$ of stationary sensing									R_{STC}
$s_i \backslash t_j$	t_1	t_2	t_3	t_4	t_5	t_6	t_7	t_8	
$s_A s_B$	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5
$s_A s_C$	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5
$s_B s_D$	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5

(e) $R_{SC}(j)$ of hybrid sensing									R_{STC}
$s_i v_i \backslash t_j$	t_1	t_2	t_3	t_4	t_5	t_6	t_7	t_8	
$v_1 s_B$	0.5	0.5	0.5	1	0.5	0.75	0.5	0.5	0.594
$v_2 s_C$	0.5	0.25	0.5	0.75	0.25	0.5	1	0.25	0.5
$v_3 s_D$	0.25	0.75	0.75	0.25	0.5	0.75	0.5	0.5	0.531

Figure 1. Spatial and spatiotemporal coverage ratios of stationary, opportunistic vehicular and hybrid sensing, with two sensors, $G_s = 2 \times 2\,(\{A, B, C, D\})$, $G_t = T/8$, and candidate vehicles $V = \{v_1, v_2, v_3\}$.

Definition 2 : The number of sensors N **.** In a sensing task, only a limited number of sensors can be used to complete the task due to budget limitations. For instance, in Figure 1(b) shows the base cells that each vehicle v_i visits at each time t_j. In this case, there are three candidate vehicles (V = $\{v_1, v_2, v_3\}$), but only two vehicles might get recruited due to budget limitations, such that the number of sensors is $N = 2$ in this monitoring task. Figure 1(c) shows all three possible combinations of choosing two vehicles out of the three. Similarly, Figure 1(d) shows results for two stationary sensors deployed alternatively in A, B, C or D. Figure 1(e) shows results for one stationary sensor and one vehicular sensor.

Definition 3 : Unit cell coverage $I_{i,j}$**.** $I_{i,j}$ represents whether the unit cell s_i is covered in time period t_j or not. The equation is defined as:

$$I_{i,j} = \begin{cases} 1 & \text{if } s_i \text{ is covered by at least one sensor during } t_j \\ 0 & \text{otherwise} \end{cases} \tag{1}$$

Definition 4: Spatial coverage ratio R_{SC}**.** Ideally, each unit cell is expected to have at least one sensor (or one vehicle passing) to monitor the requested phenomenon. R_{SC} is defined as the proportion of spatial coverage at every time period. The number of grid cells covered at time period t_j is denoted as SC_j, and defined as follows:

$$SC_j = \sum_{i=1}^{|S|} I_{i,j} \tag{2}$$

Based on Equation 2, R_{SC} at a time period t_j can be represented as follows:

$$R_{SC\,j} = \frac{SC_j}{|S|} \tag{3}$$

In OVS, to calculate SC, vehicle trajectories are analysed to obtain the vehicles trajectory matrix M_v. For example, in Figure 1(b), vehicle v_1 drove through base cells B and D in time period t_5, i.e., $SC_5 = 2$, $R_{SC5} = 0.5$. Similarly, SC and R_{SC} can be computed for multiple sensors. For example, Figure 1(c) shows the spatial coverage ratio of two vehicles at each time period. In SS, R_{SC} is constant during the sensing time T and only depends on the number of sensors and their (fix) distribution over all base cells. For instance, if sensors are placed in base cells A and B, the R_{SC} is always 0.5 (Figure 1(d)). In the following we assume an optimal distribution, i.e., no more than one sensor per base cell. In a similar way, the R_{SC} of HS formed by one stationary sensor and one vehicle is shown in Figure 1(e).

Definition 5: Spatio-temporal coverage ratio R_{STC}. R_{STC} is defined as the average coverage ratio of base cells during time period T ($T = \{t_1, t_2, ...t_n\}$). Formally, it is defined as:

$$R_{STC} = \frac{\sum_{j=1}^{|T|} R_{SCj}}{|T|} \tag{4}$$

As shown in Figure 1(c) and (d), R_{STC} of v_2 and v_3 is 0.666 in OVS, while R_{STC} of two stationary sensors in any two of the four base cells is always 0.5.

2.2 Hybrid sensing framework

For a given number of sensors, the best spatio-temporal coverage may not be obtained by SS or OVS alone but with a combination of the two. To achieve a maximum spatio-temporal coverage with a limited number of sensors, an optimized HS deployment framework is proposed. We formulate the HS deployment problem as an optimization problem (Section 2.2.1). Then, a genetic algorithm is proposed to solve the optimization problem (Section 2.2.2).

2.2.1 Problem formulation For the problem formulation, the input includes G_s, G_t, N, and the historical trajectories of candidate vehicles. So

Given:

- A total of m base cells $S = \{s_1, s_2, ..., s_m\}$, depending on G_s;
- q candidate vehicles in the pool from which $|V'|$ vehicles can be recruited for the sensing task, $V = \{v_1, v_2, ...\ v_q\}$ and $|V'| \leq q$.
- N, the number of sensors (stationary or/and vehicular sensors) that can be afforded for a given budget;
- the historical vehicle trajectory matrix M_v according to q, G_s and G_t;

then the objective of the problem is to achieve maximum spatio-temporal coverage R_{STC}:

Objective: Select a subset of base cells $S' \subset S$ to place stationary sensors, and a set of candidate vehicles $V' \subset V$ such that:

$$S' = \underset{S' \subset S}{argmax}\, R_{STC}(S).$$

The only constraint is the number of sensors N:

Subject To: $|V'| + |S'| = N$.

Note that the optimal sensing deployment does not always require a mix of stationary and vehicular sensors. Single-mode sensing deployment might also satisfy the objective.

2.2.2 Genetic algorithm design In this study, we mainly focus on how many stationary sensors and/or vehicular sensors should be deployed, and where the stationary sensors should be placed. Vehicle recruitment optimization has been discussed in previous works (He et al., 2015, Zhao et al., 2015). In this study, we only focus on the deployment of stationary sensors ignoring vehicle selection.

Each base cell has two states, *with* or *without* stationary sensors. As the time complexity of working out the optimal solution is $O(2^{|S|})$, the problem above is an NP-hard problem. Thus, to solve the problem, it is necessary to trade off between complexity and optimality. The genetic algorithm (GA), a classic evolutionary algorithm for optimization, is inspired by the process of natural selection of the fittest (Goldberg and Holland, 1988, Holland et al., 1992). On one hand, the algorithm can find various alternative solutions in the solution population. On the other hand, the combination of directional search and random search in the genetic algorithm provides a good trade-off between finding the optimal solution and limiting the search space. Owing to these characteristics, the genetic algorithm has been extensively applied to objective optimization problems (Kim et al., 2008, Tian et al., 2016). It has also been applied to optimize urban monitoring for selecting vehicles in OVS (He et al., 2015). In the genetic algorithm, three key issues need to be addressed: genetic representation, population initialization, and genetic operators (including crossover, mutation, and selection).

Genetic representation encodes the candidate solutions of an optimization problem into variable arrays called gene strings. For the optimization problem of HS deployment, each potential solutions is represented as a gene string whose length equals to the number of base cells. For each character in the string, we use 1 to indicate a stationary sensor is placed in the base cell and 0 otherwise. For instance, in Figure 2, G_s is 3×3 (i.e., the number of base cells is 9). The string *(0,1,1,0,1,0,0,1,1)* stands for stationary sensors being placed in base cells s_2, s_3, s_5, s_8 and s_9. The fitness (f) of each individual gene string is represented by R_{STC} of the corresponding combination of stationary and vehicular sensors. The larger the fitness f, the better the individual.

Figure 3 shows the process of GA. First, a certain number (*population size*) of potential solutions, each representing a placement scheme for stationary sensors, are randomly generated as the initial population (i.e., the first generation). Then in subsequent iterations, all the individuals in the current generation crossover in pairs to generate new individuals, simulating the genetic recombination process. For instance, as shown in Figure 2, the genes in s_4 to s_6 are crossed for these two solutions, generating two new individuals. Note that crossover may generate invalid solutions if the sensor number constraint is violated. To keep the number of sensors fixed in each solution, any increase or decrease in the number of stationary sensors in the crossover gene segment is compensated for by removing or adding a stationary sensor from the other gene segments.

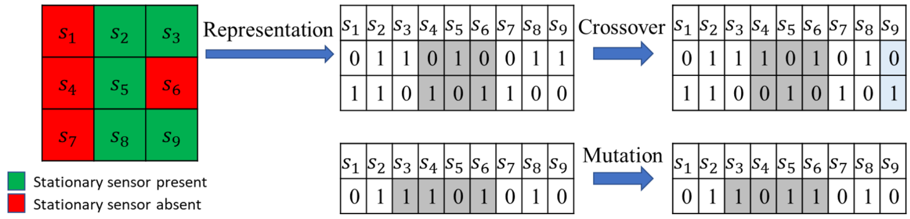


Figure 2. An example of representation, crossover and mutation in the genetic algorithm.

For instance, in Figure 2, after crossover, the first new individual will have an additional stationary sensor, so a randomly selected gene character encoded as 1 (here s_9) is changed to 0. Similarly, the second new individual will have one less sensor, so the gene in s_9 changes to 1 from 0. This step guarantees the number of stationary sensors remain unchanged for each new individual, thereby avoiding invalid solutions. After crossover, each new individual has a certain probability of mutation depending on *mutation rate*, i.e., the content of a solution is changed randomly, to simulate the genetic drift in nature. For instance, in Figure 2, the gene characters from s_3 to s_6 are reversed after mutation. At the end of the iteration, we employ the tournament selection method (Miller et al., 1995) to keep only a proportion of better individuals as the new generation for the next iteration and discard the rest by ranking individuals in order of their fitness. To be specific, in the tournament, several individuals in the generation are randomly selected to form a group. After a certain number of groups are formed, solutions with the highest fitness (R_{STC}) in each group remain to generate the next generation population and others are discarded (see Section 3.2.2 for detailed parameter settings). Finally, in the last generation (final iteration), the best individual with the highest fitness is chosen as the best solution representing the optimized HS deployment.

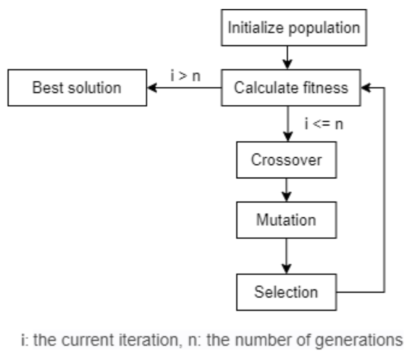


Figure 3. The flowchart of a genetic algorithm.

3. CASE STUDY AND RESULTS

This section presents the results of the proposed methods applied to a case study of Shanghai, China. Firstly, the study area and data are introduced in Section 3.1, and then the results of the case study are shown in Section 3.2.

3.1 Study area and data

In the case study, the study area (i.e., the target area of the sensing task) is the Shanghai land administrative region (within latitude $30°42'$ to $31°52'$ N, and longitude $120°52'$ to $121°58'$ E), the most populous city in China. It is an international center of economics, trade, science and technology, and has 16 administrative districts with a total area of 6340.5 km^2. Monitoring changing phenomena in this city is important for policymakers and city managers to make decisions, for scientists to explore urban changes, and for industries to develop novel services.

To explore the spatio-temporal coverage of OVS, we use a large-scale dataset of taxi GNSS trajectories in Shanghai, which are provided by Qiangsheng, a large and city-owned taxi company based in Shanghai. The dataset contains the GNSS trajectories of more than 12,000 taxis during the period of April 1 to April 7 (Sunday to Saturday) (Table 1). The GNSS sampling frequency is about 10 s. Each GNSS recording is denoted by a tuple (taxi ID, timestamp, longitude and latitude).

To facilitate the analysis, we conduct data preprocessing according to the following five steps:

- **Step 1:** Removing all trajectory points that are located outside of the target area.
- **Step 2:** Converting coordinates to the World Geodetic System 1984 as a common spatial reference system.
- **Step 3:** Assuming a sensing frequency of 60 s, i.e., resampling each trajectory at 60 s intervals.
- **Step 4:** To explore the R_{STC} of SS and OVS in different sensing tasks, a number of sensing tasks are generated. We generate 7000 different tasks with G_s ranging from 10×10[1] to 160×160, G_t from 1 h to 12 h and N ranging from 1 to 1000. Table 1 summarises the requirements of these tasks.
- **Step 5:** Combining historical vehicle trajectories with G_s and G_t, vehicle trajectory matrix is generated for each task.

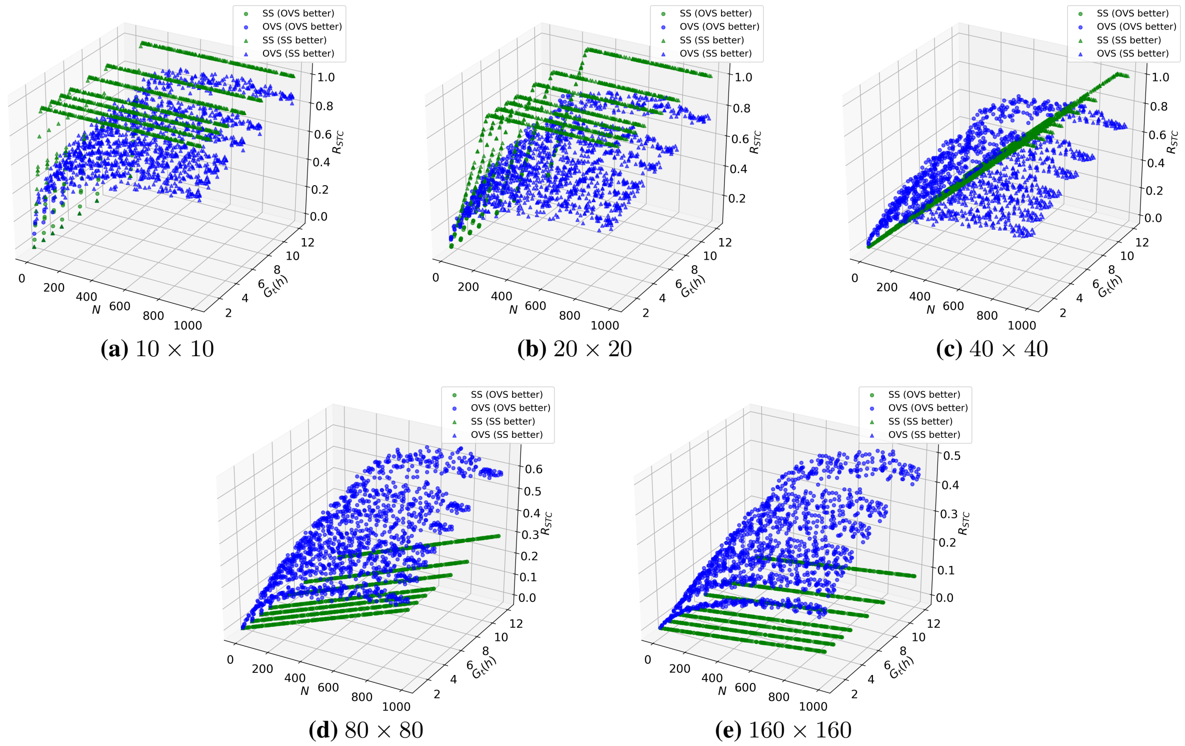
Dataset	Taxi trajectories
Period	1-7 April 2018 (Sunday to Saturday)
Time interval after data preprocessing	1 min
# taxis in the dataset	12025
G_s (base cells)	10×10, 20×20, 40×40, 80×80 and 160×160
G_t (h)	1, 2, 3, 4, 6, 8 and 12
N	1 to 1,000

Table 1. Data and experimental setup.

3.2 Results

Results are presented in four parts. First, the R_{STC} of SS and OVS are calculated and compared (Section 3.2.1). Second, the performance of the proposed HS framework is shown by comparing its solution with SS and OVS in terms of spatio-temporal coverage (Section 3.2.2). Then, the reliability and validity of HS proposed by our framework is evaluated (Section 3.2.3).

[1] The minimum bounding box of the target area is divided into 10 rows and 10 columns resulting in 100 cells



(a) 10×10 **(b)** 20×20 **(c)** 40×40

(d) 80×80 **(e)** 160×160

Figure 4. The ratio of spatio-temporal coverage in stationary and opportunistic vehicular sensing for various tasks.

3.2.1 Analysis of R_{STC} in SS and OVS The R_{STC} of SS and OVS for various tasks is calculated using seven days vehicle trajectories (i.e., the sensing cycle for all tasks is seven days) (Table 1) based on Equations 1 to 4. Figure 4 shows the R_{STC} of 7000 tasks with various spatial, temporal, and budget task requirements. The x-axis, y-axis and z-axis indicate N, G_t and R_{STC}, respectively. The green and blue scatters correspond to SS and OVS, respectively. Meanwhile, the circles represent tasks where the R_{STC} of OVS is superior to that of SS, while the triangles represent tasks where SS can achieve a higher spatio-temporal coverage. Intuitively, for a fixed number of sensors, R_{STC} is higher when the spatio-temporal granularity is coarser. In terms of the same spatio-temporal granularity, when the number of sensors is increased, the R_{STC} of both SS and OVS becomes larger. However, when the number of sensors reaches the number of base cells in the target area, R_{STC} of SS reaches the maximum (i.e., R_{STC} = 1) and does not increase with the increase of sensors any further (Figure 4 (a) to (c)).

By comparing the R_{STC} of SS and OVS, it is revealed that OVS is not always better than SS (Figure 4). When the spatial granularity of a task is coarse, a small number of stationary sensors can cover the entire target area, while OVS cannot ensure that vehicles pass each base cell at each time interval due to the arbitrary nature of the vehicle trajectories. For instance, for a spatial granularity of 10×10 base cells (which is equivalent here to a total of 75 base cells since 25 base cells are located on water or outside the target area), 75 stationary sensors are enough to monitor the whole area, while the R_{STC} of OVS with 1000 vehicles can only reach close to 0.9 (Figure 4 (a)). On one hand, this is because vehicles can only travel along roads, but in rural areas where roads are sparse, there may be fewer roads or even no roads in some of the base cells. On the other hand, there are fewer vehicles in the suburbs than in the city centre. Thus, few vehicles or no vehicle pass by these base cells. However, for tasks with the denser spatial granularity, OVS becomes increasingly advantageous. For instance, when G_s is 80×80 or 160×160, due to the limited number of sensors, OVS is advantageous, obtaining a higher spatio-temporal coverage (Figure 4 (e)).

3.2.2 Performance of the hybrid sensing framework To demonstrate the performance of the HS framework, we assume historical trajectories of candidate vehicles from the past four days (1-4 April 2018) are known. We compare the R_{STC} of the designed HS with that of SS and OVS for various tasks. Six tasks with different G_s and N are selected from the pool of tasks generated in the previous experiment (Section 3.2.1) as shown in Table 2, consisting of three tasks (Task 1 to 3) where SS achieved a higher spatio-temporal coverage and three tasks (Task 4 to 6) where OVS achieved a higher spatio-temporal coverage. For SS, R_{STC} depends only on G_s and N, thus it is the same in each iteration. For OVS, since any candidate vehicle could be selected for the task, we randomly select vehicles, and calculate R_{STC} in each iteration. We then take the maximum R_{STC} over all iterations. For the hybrid approach, the largest R_{STC} in each generation is the result of the iteration. After many tests, the following parameter settings were empirically found appropriate: the number of iterations is 200; the mutation rate is 0.25; the immigration rate is 0.2; the population size is 120; the number of groups and the number of members in each group is 20 and 10 for tournament selection, respectively.

Table 2 shows R_{STC} of six tasks. In Task 1, the result of HS is consistent with SS, i.e., the maximum spatio-temporal coverage is achieved by deploying only stationary sensors and no vehicular sensors are needed. Compared to SS, R_{STC} of HS improves by 20.31 % for Task 3, and 17.33 % for Task 2. For tasks where OVS can obtain a higher spatio-temporal coverage than SS, HS does not always outperform OVS. For instance, OVS can obtain a higher spatio-temporal coverage without stationary sensors for Task 6, so no stationary sensor is deployed

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	Task 1	Task 2	Task 3	Task 4	Task 5	Task 6
G_s	10×10	20×20	40×40	40×40	80×80	160×160
G_t	6 h	6 h	6 h	6 h	6 h	6 h
N	75	200	600	300	300	300
R_{STC} of SS	1	0.75	0.64	0.32	0.09	0.02
R_{STC} of OVS	0.64	0.53	0.56	0.47	0.37	0.26
R_{STC} of HS	1	0.88	0.77	0.55	0.37	0.25
# vehicles in HS	0	23	92	155	293	300
# stationary sensors in HS	75	177	508	145	7	0

Table 2. Six tasks and the ratio of spatio-temporal coverage in stationary, opportunistic vehicular and hybrid sensing.

by the framework proposed. Meanwhile, for Task 5, only a few stationary sensors are placed, and R_{STC} of optimized HS is almost the same as R_{STC} of OVS. However, this does not mean that OVS is superior to HS for tasks where OVS outperforms SS. For Task 4, HS improves R_{STC} by 17.02 % compared to OVS. To sum up, when G_s is coarse, with an adequate number of sensors SS can achieve higher spatio-temporal coverage than OVS and the optimized HS allocates only stationary sensors. However, when the provided sensors cannot cover all base cells, the optimized HS can achieve a higher spatio-temporal coverage than single-mode sensing, i.e., SS or OVS. When G_s is fine, it is not always feasible to provide stationary sensors covering all base cells due to the limited budget. Hence, the advantages of SS diminish, ane more vehicular sensors will be needed. For some tasks with a very fine G_s requirement, OVS is slightly better than HS. The framework we proposed can determine not only how many stationary and vehicular sensors are needed in HS (Table 2), but also which base cells stationary sensor should be placed in. Figure 5 shows the optimal placement of the stationary sensors for the six tasks determined by the genetic algorithm. The green color means a stationary sensor needs to be placed in the base cell, while the red color means the base cell does not need a stationary sensor. It can be seen that stationary sensors are mainly deployed close to the boundaries of the target area – areas not well served by vehicles.

3.2.3 Validation When we apply the proposed HS framework to optimize the sensor deployment, we predict the spatio-temporal coverage based on historical vehicle trajectories. But due to the arbitrary nature of vehicle trajectories, the predicted spatio-temporal coverage may not reflect the actual sensing coverage during the task execution. Therefore, we need a validation of the assumption that vehicles selected based on their historic trajectories would achieve a sensing coverage close to predictions. To validate this assumption, we compare the predicted coverage from historical trajectories with the actual coverage obtained from current trajectories.

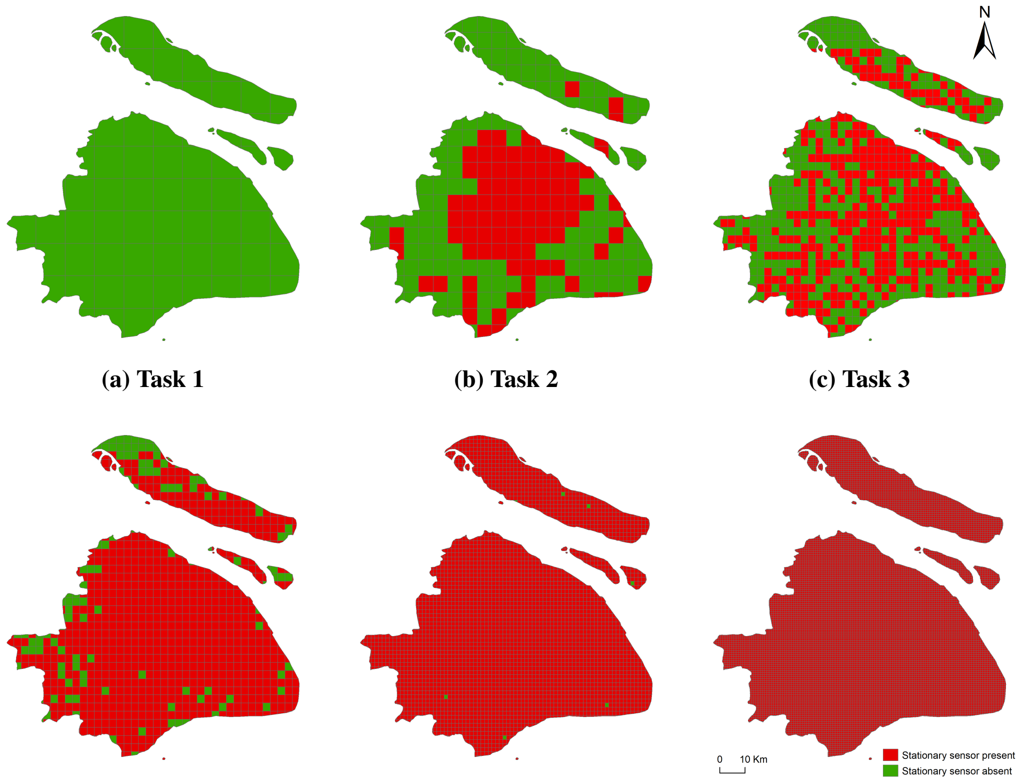
In Section 3.2.2, the deployment of HS was made using trajectories over four days (1-4 April 2018). We will now validate the coverage estimates using trajectories over the next three days (5-7 April 2018), supposing that the sensing task is scheduled for any of these days. We will focus on the reliability and validity of these estimates, assuming that sensing cycles of these tasks are one day (5 April 2018), two days (5-6 April 2018) and three days (5-7 April 2018). The actual R_{STC} in the sensing cycle is compared with the estimated R_{STC} from the HS deployment framework for Tasks 2 to 5 where mixed-mode sensing achieves higher R_{STC}.

Two deployment schemes according to the deployment designed by the proposed framework are evaluated. HS-I is the scheme where the selection of vehicles executing the sensing task and the placement of stationary sensors are defined according to the HS deployment; HS-II is the scheme where only the placement of stationary sensors and the number of vehicles are defined according to the HS deployment, whereas vehicles are randomly selected. To evaluate the generalization of the framework for tasks with multiple sensing cycles, R_{STC} of the HS is calculated in three sensing cycles. For HS-II where vehicles are randomly selected, we conducted 200 tests to calculate the mean value of R_{STC} to reduce bias. In terms of OVS, we select the same vehicles for the selected tasks, and calculate R_{STC} of OVS in three sensing cycles. For SS, coverage is independent of vehicle trajectories, so it does not change.

Figure 6(a)-(c) show R_{STC} of SS, OVS and HS during the deployment (based on vehicle trajectories from 1-4 April 2018) and sensing task execution (based on vehicle trajectories from 5-7 April 2018). The green bars correspond to SS; the blue bars with and without grey lines correspond to OVS at deployment and at sensing task execution, respectively; the pure red bars correspond to HS at deployment, the red bars with grey lines and grey grids indicate HS-I and HS-II during task execution, respectively. Error bars on red bars with grey grid represent the standard deviation of R_{STC} of HS-II. Overall, HS can obtain higher spatio-temporal coverage than OVS and SS, regardless of employing HS-I or HS-II, except for Task 5. More importantly, when the vehicle selection is based on historical trajectories (during deployment), the predicted spatio-temporal coverage is very close to the actual coverage obtained from current trajectories (during task execution), demonstrating the validity of the predictions obtained from historical trajectories. In addition, comparing R_{STC} values for different sensing cycles reveals that R_{STC} does not change significantly for different sensing cycles. This demonstrates that the proposed framework is not sensitive to the sensing cycle, so it can be applied to tasks with various sensing cycles. For Task 5, R_{STC} of HS is very similar to that of OVS during the optimal deployment, so spatio-temporal coverage obtained by HS-I is still similar to OVS in task execution. However, R_{STC} of HS-II is slightly lower than that of OVS. This is because the selection of vehicles and the selection of stationary sensor locations is a coupled process in optimal deployment. The placement of stationary sensors is optimized based on vehicle selection, which also shows that HS-I is consistently superior to HS-II. To sum up, the proposed optimization framework for HS deployment produces valid estimates of spatio-temporal coverage and can be generalized to tasks with various sensing cycles.

4. CONCLUSIONS

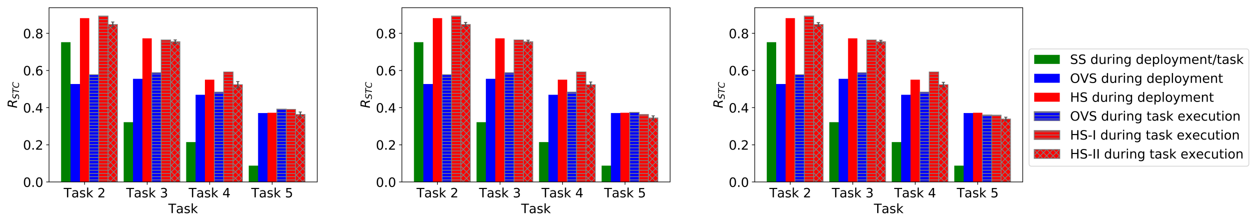
This study explores the spatio-temporal coverage of SS and OVS for various tasks, and proposes a HS framework to improve the sensing coverage. Firstly, we calculated and compared the spatio-temporal coverage of SS and OVS for various tasks with various spatial, temporal and budget requirements. The results provided a new insight showing that the spatio-temporal coverage of SS may exceed OVS for certain tasks. This study also developed a HS deployment framework integrating a genetic algorithm to co-deploy stationary and oppor-



(a) Task 1 (b) Task 2 (c) Task 3

(d) Task 4 (e) Task 5 (f) Task 6

Figure 5. The places of stationary sensors in hybrid sensing for six tasks.



(a) 1-day sensing cycle (b) 2-day sensing cycle (c) 3-day sensing cycle

Figure 6. Comparison of the ratio of spatio-temporal coverage between deployment and task execution for different sensor deployment in different tasks.

tunistic vehicular sensors, thereby reaching maximum spatio-temporal coverage. Evaluations show that the spatio-temporal coverage of optimized HS designed by our framework outperforms SS and OVS by up to 20.31 %. In tasks where SS or OVS can achieve a higher spatio-temporal coverage, the proposed HS framework also finds the single-mode sensing as the optimal solution. The validity and generalization ability for various sensing cycles are also evaluated. The results show that the performance of the proposed HS framework is superior or similar to the single-mode sensing. Our study provides fundamental guidelines on sensor network planning for urban monitoring applications.

The results of our study need to be interpreted in consideration of several limitations. First, we mainly focus on co-deploying stationary sensors in the HS framework. Although it is shown that the results are still better than SS and OVS, the optimal solution for combination of vehicles and stationary sensors cannot be produced. However, our approach also has its advantage. In real-world, we may not have candidate vehicle trajectories, but if there are other vehicle trajectories, we can still use the approach to deploy stationary sensors, and then randomly select vehicles carrying sensors (i.e., HS-II in Section 3.2.3). Second, we ignored some technical limitations of sensors during the process of urban monitoring, e.g., signal instability and inaccuracy caused by sensing devices and sensing conditions. Third, we do not take into account the difference in price between placing stationary sensors and installing vehicular sensors, and the later maintenance. In the future, we will investigate on the optimal solution for combination of vehicles and stationary sensors, and incentive reward mechanism to achieve maximum spatio-temporal coverage in terms of OVS.

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