An Optimisation-based Approach for Wireless Sensor Deployment in Mobile Sensing Environments

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***Abstract*—We consider a novel application in wireless sensor networks where mobile phones and wireless sensors can collaborate to collect sensing data. Although mobile phones can perform sensing at different locations, it is a challenge to provide stable sensing quality and availability over the entire area. One approach is to deploy stationary sensors at specific locations to maintain the sensing quality and availability. In this paper, we present a mathematical programming model to minimise the deployment cost by placing a minimum number of sensors at optimal locations. The problem is modelled by integer linear programming considering the sensing capabilities of both the mobile phones and wireless sensors. We evaluated the performance of our solution in terms of sensing quality, number of required sensors, and computation time. The results demonstrate that our approach satisfies the required sensing quality with optimal number of sensors in small sensing fields. It achieves near optimal solution with low computation time for large sensing fields.**

I. Introduction

Wireless sensor networks (WSNs) have been widely suggested for environmental protection, transportation, industrial production, health care, home safety, etc [1], [2]. They are constructed by a number of sensors that measure temperature, sound, vibration, motion, pollutants, etc. Even though individual sensors are not very expensive, a large network can have considerably high deployment and maintenance costs. In the meantime, mobile phones are increasingly popular and are often equipped with sensing capabilities, like camera, microphone, motion sensor, and GPS, which allow them to be used as sensors for different applications [3].

A number of sensing applications have emerged recently that use mobile phones to assist sensing. These applications are often referred to as participatory sensing [3] or urban sensing [4]. For example, in "What's Invasive" [5], mobile phone users are asked to take pictures of invasive species that are a threat to native plants and animals, consuming food sources, or acting as fire hazards. The data collected by the mobile phone users are uploaded to a server for aggregation and publishing. It is understood that mobile phone users, who join a sensing activity voluntarily, would enable their phones to collect sensing data for that purpose. However, the mobility and dynamic behaviour of mobile phone users make it hard to guarantee a constant level of sensing coverage and quality.

In this work, we consider a collaborative sensing system that enables mobile phones and stationary sensors to perform sensing together. Mobile phones can collect sensing data at different locations as they are carried by their users who are moving freely in the sensing field. Stationary sensors can complement the relatively dynamic sensing performance of the mobile phones. We consider a meshed network infrastructure that supports wireless communication standards, such as 3G, WiFi and Zigbee, for mobile phones and wireless sensors to report their data. The stationary sensors can be deployed at different locations to monitor the environment and human activities. Our goal is to minimise the deployment cost of stationary sensors, while maintaining satisfactory sensing quality (average of sensor measurements compared with the ground truth) in the collaborative sensing system. Moreover, we target one-time deployment of the sensors to avoid extra costs of re-configuration and re-deployment.

Our main contribution is to model and solve the one-time deployment problem for large-scale sensor networks. We model the problem using integer programming (IP). The aim is to minimise the number of sensors and to place them at optimal locations to ensure the required sensing coverage. We make use of real mobile traces collected from Disney World Orlando [6], [7] to evaluate the sensing coverage, number of sensors, and computation time of our solution.

The rest of this paper is organised as follows. In section II we present an overview of our network involving three phases of gathering data, preprocessing, and deployment of stationary wireless sensors. We present the preprocessing phase of the raw data in section III, followed by an IP model in section IV. We evaluate our model in section V, and present related works in section VI. Finally, the conclusion and future work is presented in section VII.

II. System Overview

Our deployment is designed to have three phases. In the first phase, the mobile phone users collect data in the sensing field, while GPS traces of their locations are collected every 30 seconds during a period of time (typically 10 hours up to one day). In the second phase, we analyse the collected coordinates to discover the coverage provided by the mobile phones, according to their sensing quality (preprocessing phase). In the third phase, the stationary sensors are deployed to ensure that a satisfactory total level of coverage in sensing is achieved,

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according to the sensing quality provided by the sensors in the entire sensing field.

III. Preprocessing

The raw data resulting from phase one contain GPS coordinates collected by mobile phone users. Without loss of generality, we focus on square sensing fields, and we divide the sensing field into square cells of side size $CellSize$, where $CellSize$ is typically between 20 and 200 meters. The aggregated sensing coverage, which measures the sensing quality provided by the mobile phone users, is calculated every hour for all cells. We consider that the sensing capability of both the mobile phones and the sensors are the same, as this does not limit the applicability of the placement model [8]. Moreover, the sensors are always deployed at the centres of the cells. We take the detection model of [8], where the sensing quality $z(h)$ decreases exponentially with the distance h between the target and the sensor:

$$z(h) = e^{-\gamma \cdot h},$$

where γ models the quality of the sensor and the rate at which its sensing quality diminishes with distance. Let $MaxCovRange$ be the maximum coverage range in meters that a sensor or mobile phone provides, and let B be the maximum number of cells that can be covered by a sensor in one direction, so that $B = \left\lceil \frac{MaxCovRange}{CellSize} \right\rceil$.

We define the *sensing mask* (see Figure 1) as a square matrix Z representing the coverage, provided as an integer percentage, by a sensor:

$$\begin{aligned} & \forall i, j \ (1 \leq i, j \leq 2 \cdot B - 1) : \\ Z[i,j] \quad &= \begin{cases} \lceil 100 \cdot e^{-\gamma \cdot h} \rceil & \text{if } h \leq MaxCovRange, \\ 0 & \text{otherwise;} \end{cases} \end{aligned} \tag{1}$$

where

$$h = CellSize \cdot \sqrt{(i-B)^2 + (j-B)^2},$$

is the Euclidean distance metric measuring the distance of a target at coordinates (i, j) to the sensor that is at the centre of the sensing mask, at coordinates (B, B). By construction, $Z[B, B] = 100$ and the size of the sensing mask is $2 \cdot B - 1$. In our problem, the sensor provides full coverage (value 100) *only* for the cell at which it is placed. Any cell outside the sensing mask has a coverage of zero. Figure 1 shows an example of a sensing mask Z based on the Euclidean distance metric for $MaxCovRange = 400$ meters, $CellSize = 100$ meters, and $\gamma = 0.004$, giving $B = 4$.

Given a sensing field of $N \times N$ cells (we say that it is of size N) from the GPS coordinates of the mobile phones, we compute the coverage by placing copies of the sensing mask Z on the location of each mobile phone, and sum all the coverages for the overlapping masks on each cell in the sensing field. We consider the coverage provided by the mobile phones and sensors in the sensing field as in [9]. The coverage area is the spatial extent of network covered by the sensors, which represents the total information that can be extracted from all

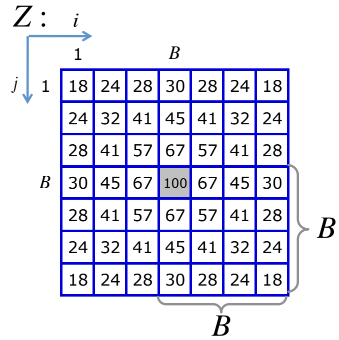

Figure 1. Sensing mask Z based on the Euclidean distance metric for $MaxCovRange = 400$ m, $CellSize = 100$ m, and $\gamma = 0.004$, giving $B = 4$.

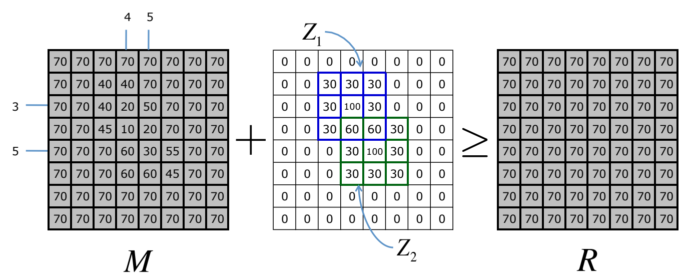

Figure 2. Two sensors placed at coordinates $(3, 4)$ and $(5, 5)$ provide satisfactory total coverage over a sensing field of size $N = 8$, where M is the coverage matrix provided by the mobile phones, and R is the requirement matrix to be satisfied for all cells.

sensors in a sensing field. Intuitively, a sensing field with a higher number of deployed sensors implies a higher reliability of the monitored data. We adopt an *additive* model to measure the aggregated sensing quality of multiple sensors in the same sensing field [9]. In contrast, in [10] a *minimum* coverage model is used, where the aggregated coverage is equal to the minimum of the coverage provided at the considered cell.

We then take the average of the coverage at each 30 second time slice over the entire duration of the experiment (see [11]). As a result, the output of the second phase is an $N \times N$ coverage matrix M, such that $M[i, j]$ is the coverage (sensing quality), given as an integer percentage, provided by the mobile phones for cell (i, j) of the sensing field.

IV. Deployment Model and Optimisation

Let R be a $N \times N$ matrix, such that $R[i, j]$ is the coverage required, given as an integer percentage, for cell (i, j) of the sensing field. Given the coverage M of the mobile phones, the required coverage R, and the sensing mask Z of sensors, our objective is to place a minimum number of stationary sensors to achieve the required coverage R for all cells. Figure 2 shows matrices M and R for a field of size $N = 8$ with a simplified sensing mask of size 3. In this example, the coverage requirement R is satisfied by deploying two sensors, at coordinates $(3, 4)$ and $(5, 5)$.

A sensor placed at cell (i, j) contributes to the coverage of the neighbouring cells according to the sensing mask Z.

Let $s[i,j]$ be a binary decision variable denoting the placement (value 1) or absence (value 0) of a sensor at cell (i,j), with $1 \leq i,j \leq N$. We first pad the matrix s on all sides with $B-1$ extra rows and columns of zeros, for the ease of presentation. Let s' be the padded matrix.

Our integer programming formulation of the deployment problem is defined as:

Inputs:

- M: Coverage provided by the mobile phones.
- R: Required coverage for the sensing field.
- Z: Coverage provided by a stationary sensor.

Outputs:

- s': Placement: $s'[i,j] = 1$ iff a sensor is placed at cell (i,j).

Objective:

$$\text{minimize} \quad \sum_{i,j=1}^{N} s'[i,j] \tag{2}$$

Such that:

$$M[i,j] + \sum_{k,\ell=1}^{2 \cdot B-1} Z[k,\ell] \cdot s'[k+i-B, \ell+j-B] \geq R[i,j] \quad \text{for all } i,j \ (1 \leq i,j \leq N), \tag{3}$$

$$s'[i,j] = 0 \quad \text{for all } i,j \in \text{padding area}, \tag{4}$$

$$s'[i,j] \in \{0,1\} \quad \text{for all } i,j \ (1 \leq i,j \leq N). \tag{5}$$

The objective function (2) is to minimise the total number of deployed sensors. The coverage constraints (3) ensure that for every cell (i,j) in the sensing field, the sum of the coverage provided by mobile phones $M[i,j]$ and the coverage provided by the stationary sensors in all the neighbouring cells is at least the required coverage $R[i,j]$. The constraints (3) are linear, as the sensing mask Z is a constant integer matrix. Just like for the construction of M (in Section III), we here use the *additive* coverage model of [9]. Constraints (4) ensure that no sensor is placed on the padding area. Finally, the placement decision variables s' are binary (constraints (5)). The model has N^2 decision variables and N^2 constraints.

V. Evaluations

We implemented the IP model in *Gurobi Optimizer* (revision 4.5.1),[1] and run under Linux OpenSuse 11.4 (64 bit) on an Intel Core i7 950 3.07 GHz with 8 MB L2 cache and 3 GB RAM. The runtime is limited to 600 seconds. We evaluated our model with the mobile traces collected by the participating visitors to Disney World (Orlando, Florida, USA) [6], [7], [12], where noise level and pictures are collected by the mobile phone users. The instance data cover an area of approximately 16 km $\times$ 8 km. For the first instance, we choose a square sensing field of 1 km $\times$ 1 km at the centre of that area. This sensing field is divided into $N^2 = 100$ cells of size 100 m $\times$ 100 m. In all other instances, we keep the same cell size, i.e. $CellSize = 100$ m, and increase N by one, so that the sensing field is expanded by $CellSize/2$ meters on each side. We also set $MaxCovRange = 400$ m and $\gamma = 0.004$, resulting in the sensing mask of Figure 1 with $B = 4$.

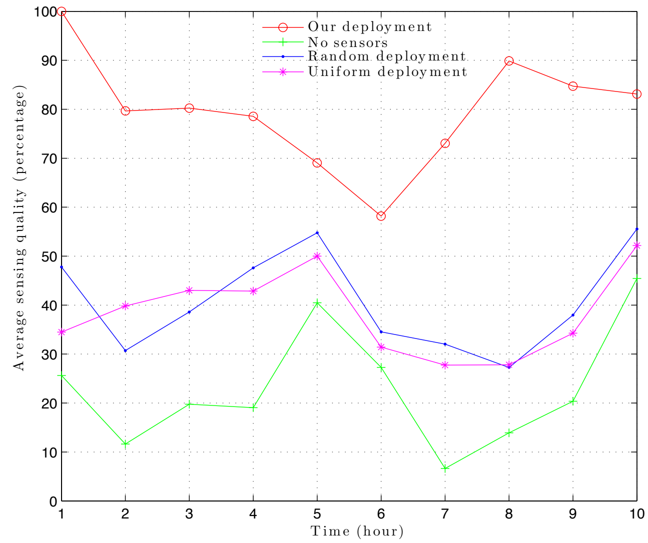

Figure 3. Average sensing quality over a ten-hour period after deploying the sensors for a sensing field of size $N = 50$, comparing our deployment versus no sensors, random, and uniform deployment with an equal number of sensors, and required sensing coverage of 70%.

Figure 3 compares the average sensing quality of our deployment versus no sensor, random, and uniform deployment of sensors for a sensing field of size $N = 50$ over a ten-hour period after deploying the sensors with a required sensing coverage of 70% (the quantiles are not shown for space reasons). We used an equal number of sensors computed by our deployment for the random and uniform deployment. In our experiment, the sensors are deployed according to a one hour time slot in the beginning of the experiment, and the average sensing quality is calculated every hour, considering the coverage provided by the mobile phones and the coverage provided by the stationary deployed sensors for each time slot of one hour. The results show that our one-time deployment achieves a significantly better average sensing quality after deploying the sensors. Our deployment guarantees the required sensing coverage of 70% for all cells in the sensing field during the first three and last four time slots. However, we cannot guarantee the required sensing quality during the fourth and fifth time slot, which is due to strong variation in the mobility of the mobile phones during this period, also the number of mobile resources drops at the fifth time slot.

Figure 4 shows the computed number of sensors for deployment, varying the required coverage over all the cells. It also compares the results of three different sensing fields with size of $N = 10$, 30, and 50, respectively. We find that the number of sensors increases linearly with required coverage. Also, a larger sensing field requires more sensors to achieve the same sensing coverage.

Figure 5 compares the computed number of wireless sensors

[1] Available from http://gurobi.com

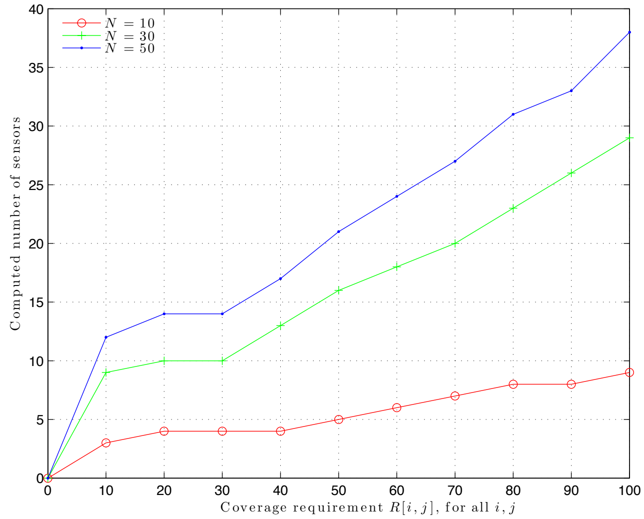

Figure 4. Computed number of wireless sensors, varying the required sensing coverage.

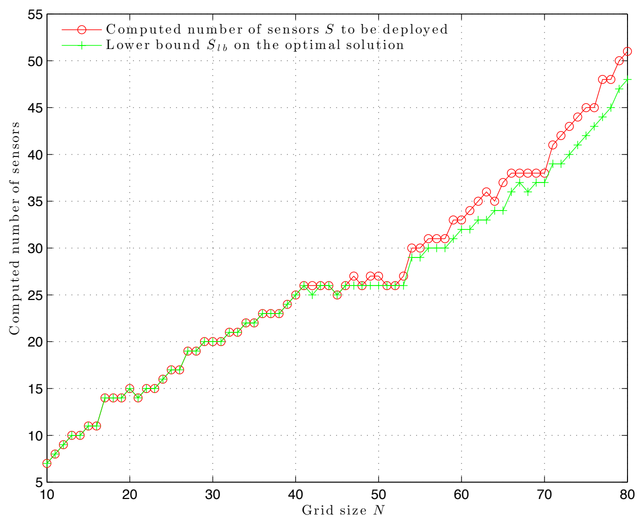

Figure 5. Computed number of required wireless sensors compared to a lower bound S_{lb} on the optimal solution, varying the size of sensing field, and using a required sensing coverage of 70%.

to be deployed to a lower bound S_{lb} on the optimal solution, varying the size of the sensing field, with a required sensing coverage of 70%. From the results, our IP model always finds the optimal solution up to $N = 41$. The solution quality for sensing fields with $N \geq 42$ is also very close to the optimum.

Table I presents the results of the same experiments starting from grid size $N = 10$ up to $N = 80$, and a required sensing coverage of 70%. Column S_{lb} shows the computed lower bound (using the dual form of the IP model) on the number of sensors to be deployed as an indication of the solution optimality. The gap between the lower bound and the computed number of sensors is at most 8% in all instances even with $N \geq 42$. The columns S and Time show respectively the computed number of sensors to be deployed

N	S_{lb}	S	Time	N	S_{lb}	S	Time	N	S_{lb}	S	Time
10	7	7	0.02	34	22	22	2.79	58	30	31	> 600
11	8	8	0.02	35	22	22	1.32	59	31	33	> 600
12	9	9	0.09	36	23	23	12.30	60	32	33	> 600
13	10	10	0.17	37	23	23	340.37	61	32	34	> 600
14	10	10	0.12	38	23	23	51.56	62	33	35	> 600
15	11	11	0.59	39	24	24	142.87	63	33	36	> 600
16	11	11	0.76	40	25	25	250.38	64	34	35	> 600
17	14	14	2.41	41	26	26	569.44	65	34	37	> 600
18	14	14	1.09	42	25	26	> 600	66	36	38	> 600
19	14	14	1.50	43	26	26	256.69	67	37	38	> 600
20	15	15	1.07	44	26	26	356.87	68	36	38	> 600
21	14	14	1.02	45	25	25	201.83	69	37	38	> 600
22	15	15	3.71	46	26	26	46.94	70	37	38	> 600
23	15	15	1.42	47	26	27	> 600	71	39	41	> 600
24	16	16	15.22	48	26	26	375.42	72	39	42	> 600
25	17	17	2.04	49	26	27	> 600	73	40	43	> 600
26	17	17	1.69	50	26	27	> 600	74	41	44	> 600
27	19	19	77.85	51	26	26	438.50	75	42	45	> 600
28	19	19	4.04	52	26	26	28.19	76	43	45	> 600
29	20	20	36.35	53	26	27	> 600	77	44	48	> 600
30	20	20	2.76	54	29	30	> 600	78	45	48	> 600
31	20	20	3.12	55	29	30	> 600	79	47	50	> 600
32	21	21	6.35	56	30	31	> 600	80	48	51	> 600
33	21	21	5.19	57	30	31	> 600				

Table I
THE EXPERIMENT RESULTS REPRESENT THE GRID SIZE N, AND THE COMPUTED (BY IP) LOWER BOUND S_{lb} ON THE NUMBER OF SENSORS. COLUMN S SHOWS THE COMPUTED NUMBER OF SENSORS TO BE DEPLOYED. THE TOTAL TIME FOR THE OPTIMISATION IS GIVEN IN THE TIME COLUMN IN SECONDS, WITH A TIMEOUT OF 600 SECONDS. THE REQUIRED SENSING COVERAGE IS 70% FOR ALL CELLS IN THE SENSING FIELD.

and the total time of the optimisation in seconds. The results indicate that the optimal solutions can be computed efficiently with much less than 600 seconds for small sensing fields ($N \leq 35$). For large sensing fields, near optimal solutions can also be achieved in 600 seconds.

VI. RELATED WORK

The concepts of data mules and mobile sinks have been explored to improve data collection in wireless sensor networks. *Data Mules* [13] have been proposed as a three-tier architecture to collect data in sparse sensor networks using moving entities. Similarly, mobile sinks have been suggested to collect data from the sensors and forward the data to the base station as mobile relays [14]. Various algorithms have been proposed to control the movement of the mobile sinks in order to optimise the performance in data collection [15], [16]. Different from the work above, we consider the mobile phones carried by people with independent and uncontrollable mobility. Also, we focus on optimising the deployment cost of stationary sensors instead of controlling the mobility of the moving entities.

The deployment problem of wireless sensors networks has been widely studied. Dhillon et al. [8] proposed two greedy algorithms for wireless sensor deployment based on a probability model in a grid sensing field. Chakrabarty et al. [17] proposed a deployment scheme to reduce the deployment cost for heterogeneous kinds of sensors. Apart from that, wireless sensors have recently been suggested to improve the sensing quality in collaboration with the mobile phones [11]. Although a simple version of the deployment problem has been tackled by us in [11], it was only solved by a heuristic algorithm and only a small instance (size $N^2 = 100$) was experimented with. In this paper, we introduce an IP model to solve the deployment problem, which can lead to near optimal solutions for a much larger sensing field (size $100 \leq N^2 \leq 6400$).

Although sensor coverage with mobile sensors has been investigated, the existing work mainly focused on deploying or controlling the mobility of mobile sensors. Wang et al. [18] proposed two bidding protocols for the movement of mobile sensors to avoid the coverage holes from stationary sensors. Similarly, Gupta et al. [19] proposed a stochastic sensor movement strategy, which can monitor a geographical area by a small number of mobile sensors. Different from their work, we consider mobile phones with uncontrolled mobility and improve the sensing performance by deploying stationary sensors at optimal locations.

VII. Conclusions and Future Work

In this paper, we presented a mathematical programming model for sensor deployment in a collaborative sensing environment with both mobile phones and stationary sensors. We model the problem by integer programming, considering the sensing coverage of both the mobile phones and the wireless sensors. Our solution provides satisfactory sensing coverage as specified by the application requirements, while minimising the number of wireless sensors in deployment. We evaluated our model using real mobility traces and proved the optimality of the solutions for small sensing fields. The results also showed that close to optimal solutions can be achieved for large sensing fields within short computation time. For the future, we are interested in investigating how our model can scale by introducing obstacles and solving the problem in three dimensions. We also consider modelling the problem by adopting other coverage models than the one used in this work (namely *additive* coverage model) and compare the performance and quality of the results.

Acknowledgments

This research is sponsored by the Swedish Foundation for Strategic Research (SSF) under research grant RIT08-0065 for the project *ProFuN: A Programming Platform for Future Wireless Sensor Networks*.

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