Adaptive Collaborative Sensing Using Mobile Phones and Stationary Sensors

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***Abstract*—Wireless sensors networks (WSNs) have been widely deployed for habitat monitoring, structure monitoring, fire detection and object tracking applications. Although WSNs can provide continuous sensor readings, the battery, computation and communication resources are limited in wireless sensors. Recently, mobile phones have been suggested to be utilized as sensors in various participatory sensing campaigns. However, it is hard to guarantee the sensing quality due to the mobility and sensing quality of individual mobile participants.**

In this paper, we consider a collaborative sensing paradigm which utilizes both mobile phones and stationary sensors to perform sensing. It enables mobile phones and stationary sensors to complement each other in order to achieve better overall sensing quality and reduce the energy consumption of wireless sensors. We propose an adaptive collaborative sensing algorithm that can coordinate sensing among the available mobile users and the stationary sensors in the area of interest. Mobile phones are given higher priority to perform sensing, while stationary sensors will be enabled if the required sensing quality is not reached. Our algorithm is adaptive to the mobility and sensing quality of the mobile phones, as well as the unusual events in the environment. Simulations are conducted to evaluate the sensing quality, the number of mobile phones and stationary sensors enabled with our algorithm.

I. Introduction

Wireless sensor networks (WSNs) are widely proposed for various environmental monitoring applications, such as habitat monitoring, structure monitoring, health monitoring, object tracking and fire detection [1], [2]. Traditional WSNs involve a number of small and resource-limited stationary sensors carefully deployed at fixed locations. The battery and network lifetime are of great concern, given that the wireless sensors are not regularly charged or frequently maintained by human beings [3].

With the popularity of mobile phones, research work such as participatory sensing [4], [5] and urban sensing [6], [7] have attracted increasing attention. Mobile phones are suggested to be used as sensors to perform sensing in the environment. Many mobile phones are equipped with various sensing capabilities nowadays, such as noise, motion, location sensors, etc. Since the phones are regularly charged, a number of participatory sensing applications have emerged in recent years [5], [7]. However, the randomness of user movements and behaviors may bring difficulty in guaranteeing satisfactory coverage and sensing quality in the network.

In this paper, we suggest that stationary sensors and mobile phones can perform sensing collaboratively to reduce the energy consumption of stationary sensors and prolong the network lifetime. The collaboration between stationary sensors and mobile phones can provide better sensing quality, especially in case of unusual events or sensor failures in the network. The goal of this work is to provide satisfactory sensing quality adaptively to the environment change and the mobility of mobile participants. The sensing rate of stationary sensors will be reduced if there are enough sensing quality provided by the mobile participants. The sensing quality provided by the mobile phones and stationary sensors will also be adjusted adaptively to the change of the environment. We propose an adaptive sensing algorithm for mobile phones and stationary sensors to minimize the energy consumption of stationary sensors and mobile phones, while providing satisfactory sensing quality for the system.

The paper is organized as follows. In section II, we review the related work. We give the network and sensing models in Section III and the problem formulation in Section IV. Section V present the system overview and the adaptive sensing algorithm for mobile phones and stationary sensors. In section VI, we evaluate the performance of our solution through simulations using real mobility traces. Finally, we conclude the paper in section VII.

II. Related Work

Participatory sensing have been studied to promote mobile phone-based sensing in urban areas, factories, country parks, etc [4], [5], [7]. The proposed sensing campaigns can coordinate across a potentially large number of participants over wide spans of space and time. Research topics on participatory sensing spread over privacy mechanisms [8], coordination among mobile participants [9] and performance evaluation for feedback, incentives and recruitment [10], etc. The above work focus on sensing with only mobile phones, while our work considers sensing perform collaboratively with both stationary sensors and mobile phones. We focus on reducing the energy consumption of stationary sensors and mobile phones and providing satisfactory sensing quality to users.

Some related work on adaptive samplings have also been proposed to decrease the energy consumption of wireless sensors and to prolong the network lifetime. Gedik et al. [11] suggested to collect data using a dynamically changing subset of nodes as samplers, whereas the values of the nonsampler nodes are predicted through a probabilistic model. Similarly, Willett et al. [12] achieved adaptive sampling by selecting activating sensors with the backcasted information from the fusion center. Apart from the spatial approaches, some adaptive sampling approaches on the temporal domain have also been considered. Kho et al. [13] proposed a decentralized algorithm to minimize the uncertainty of sensing data, subject to the constraint of a limited number of samples taken per node. Different from the above work, we consider sensing in a heterogeneous network with both stationary sensors and mobile phones. The mobility and sensing quality of mobile phones have to be taken into account, in order to provide enough sensing quality and reduce the energy consumption of the stationary sensors.

The coverage issue in traditional WSNs has been studied extensively [14], [15], where scheduling algorithms have been proposed to maximize the network lifetime while maintaining more predefined coverage degree. Spatial-temporal coverage optimization has been investigated by Changlei et al. [16] for WSNs. J. Lee et al. [17] have investigated heterogeneous deployments of devices with different capabilities for sensor networks. The deployment in various network deployment environments and network operation models have been analyzed both mathematically and through simulations considering coverage degree and coverage area. B. Han et al. [18] have studied how to offload cellular traffic through opportunistic communications and investigate the target-set selection problem for information delivery in mobile social networks. Furthermore, the deployment of stationary sensors has also been explored in a mobile phones assisted sensing environment [19]. Instead of studying the deployment problem for stationary sensors, we consider how to minimize the energy consumption of nodes adaptive to the change of environment after the stationary sensors have already been deployed. This is indeed a practical problem as stationary sensors usually stay at the deployed locations for a long time, even though the environment and the sensing requirements are changing.

III. Network and Sensing Models

A. Network Model

We consider a network composed by a number of pre-deployed stationary sensors and mobile phone users that are performing sensing collaboratively in a sensing field. The stationary sensors and mobile phones are equipped with certain sensing capabilities, such as noise sensor, camera, temperature sensor, accelerometer, etc. We foresee that the sensing capability of mobile phones would further increase in the near future. Apart from built-in sensors, mobile phones can also connect to external sensors through their USB port to increase their sensing capability [19].

The sensing field is divided into a number of smaller grid cells, denoted as g_j in the following of the paper. The stationary sensors are deployed at the center of the selected grid cells, while the mobile users are free to enter, exit, and move around in the the sensing field. The mobile phones can report the sensing data to the server by GPRS or WiFi, while the stationary sensors can report the data through multihop routing or opportunistic forwarding to the nearby sink.

B. Sensing Model

We measure the sensing quality following the sensing model from [20] which calculates the detection probability of a target using physical properties of the sensors. The detection probability p_{ij} for a target in grid cell g_j from a sensor deployed in grid cell g_i is achieved assuming using a normalized full power level $\gamma_j^*(t) = 1$, i.e. The probability p_{ij} is proportional to the distance between the sensor and the target.

$$p_{ij} = \begin{cases} 1, & \text{if } r_{ij} \leq d_1, \\ e^{\beta_1 (r_{ij} - d_1)^{\beta_2}}, & d_1 < r_{ij} \leq d_2, \\ 0, & \text{if } r_{ij} > d_2 > d_1. \end{cases} \quad (1)$$

We use the values β_1=0.1, β_2=0.6, d_1=50m, and d_2=300m and r_{ij} denotes the sensor-to-target distance. For instance, the above detection probability can represent the sensing quality of a noise sensor to the target.

We consider that the mobile phones and stationary sensors share the same sensing model here. We also divide time into a number of small time intervals, i.e. $t_1, t_2, ...t_k$. The sensing quality achieved by grid cell j in the system is denoted as Q_j^t at time t. If the target grid cell g_j is covered by more than one stationary sensors or mobile phones, the combined sensing quality can be calculated by

$$Q_j^t = 1 - \sum_{\forall i \in S_j^t} (1 - p_{ij}), \quad (2)$$

where $i \in S_j^t : r_{ij} < d_2$ and S_j^t includes all sensors covering target j.

IV. Problem Formulation

Our design goal is to minimize the energy consumption of stationary sensors and mobile phones, given that satisfactory sensing quality is achieved. Since stationary sensors are not regularly charged, we assign higher priority to the mobile phones than the stationary sensors to perform sensing. It means that the stationary sensors can reduce their sensing rates if the sensing area is covered by mobile phones with enough sensing quality. Moreover, our system should provide good sensing quality adaptive to the change of environment. For instance, higher sensing quality should be achieved when there are unusual events in the network. On the other hand, the sensing quality of the system can be reduced if it is performing routine monitoring in environment without any unusual events.

Let $x_0, x_1, x_2, ..., x_k$ be the sensor readings from mobile phones or stationary sensors at time $t_1, t_2, ..., t_k$ collected in the same time interval Δt, i.e. $t_1, ..., t_k \in \Delta t$. It is observed that the sensor measurements usually fall within a range $[a, b]$ in a normal situation. To distinguish the normal situation and potentially unusual events, the server will compare the sensor readings with the expected range in a normal situation. If the sensor reading is deviated from the normal range, the server may suspect that unusual events may occur in the respective area. The required sensing quality will then be increased to provide more sensing data about the environment. We consider that the required sensing quality is REQ_Q_n for routine monitoring in normal situation. The required sensing will be increased to REQ_Q_u when there is unusual event in the sensing field, i.e. $REQ\_Q_n \leq REQ\_Q_u$.

Objective

$$\text{Minimize } \alpha m + \beta n, \tag{3}$$

Subject to

$$Q_j \geq REQ\_Q, \forall j \tag{4}$$

$$m \leq M \tag{5}$$

$$n \leq N \tag{6}$$

$$REQ\_Q = \begin{cases} REQ\_Q_n, & \text{if normal situation,} \\ REQ\_Q_u, & \text{if unusual event,} \end{cases} \tag{7}$$

where m and n are the number of sensing performed by mobile phones and stationary sensors in the respective area in a given time interval, and α and β are the weights for calculating the sensing cost using mobile phones and stationary sensors respectively. The number of sensor readings is bounded by the available sensors N, while the number of sensing performed by mobile phones is bounded by the available mobile phones M in the area. Given that stationary sensors are more constrained with their battery, our system gives higher preference to mobile phones for sensing. On the other hand, mobile phones are usually charged by their users regularly. For instance, we can set $\alpha = 0$ and $\beta = 1$ for this scenario.

V. Adaptive Collaborative Sensing With Mobile Phones and Sensors

A. System Overview

Our adaptive collaborative sensing system coordinates the mobile phone users and the stationary sensors to perform sensing in the area of interest. Figure 1 shows the work flow of our framework. In each time interval, the system aims at providing the required sensing quality REQ_Q by leveraging the available mobile phones or stationary sensors. In our design, we give high priority to mobile phones than stationary sensors as the battery of sensors are more limited and they are not regularly charged. Hence, readings from mobile phone users will be accepted in the first phase in each time interval. The accumulated sensing quality will be updated when new sensing reading arrives. At the end of each time interval, the system will check if the required sensing quality is reached by the mobile phone users. If not, the system will select and request data from the stationary sensors in order to achieve higher sensing quality.

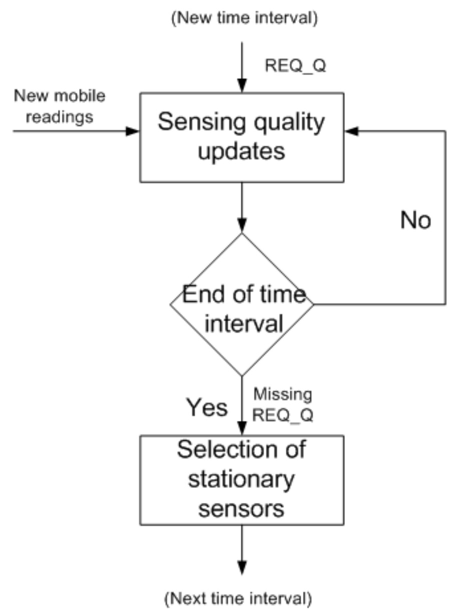

Fig. 1. The work flow of our adaptive collaborative sensing system.

We focus on the adaptive collaborative sensing algorithm for selecting mobile phone users and stationary sensors in this work. Intuitively, less stationary sensors will be enabled if there are enough mobile phone users available for sensing. Otherwise, more stationary sensors will perform sensing to increase the overall sensing quality of the system. Our algorithm will coordinate the sensing of stationary senors and mobile phones adaptively according to the available mobile phone users and the corresponding sensing quality in each time interval. Note that the required sensing quality will also be adjusted adaptively according to the change of the environment. When an unusual event occurs in the sensing field, more sensing data and higher sensing quality will be expected from the users.

B. Adaptive Collaborative Sensing Algorithm

In our algorithm, the server collects sensing data from mobile phone users in each sub-area j in each time interval. Consider the available mobile phone readings in a time interval be $x_1, x_2, ...$ with corresponding sensing quality $p_1, p_2, ...$, the server receives these mobile phone readings from the beginning of a time interval until that the required sensing quality in that sub-area is reached. More formally, the server will initialize the missing sensing quality as $missing_j = 1$ at the beginning of each time interval. Suppose that the readings $x_1, x_2, ...$ arrive in sequence along time, the server will update the missing quality for each x_i by calculating

$$missing'_j = missing_j(1 - p_{ij}), \tag{8}$$

where $missing'_j$ is the newly calculated missing quality and p_{ij} is the sensing quality provided by reading x_i about j.

Algorithm 1 Adaptive Collaborative Sensing

```
% For each time slot δt
for each time slot δt do
  missing_t = 1
  REQ_Q_t = REQ_Q_n
  for each mobile phone participant i in area j do
    if missing_t ≥ 1 − REQ_Q_t then
      Report sensing reading x_i to server
      Calculate the sensing quality p_ij
      missing_t = missing_t(1 − p_ij)
      if x_i outside normal range then
        REQ_Q_t = REQ_Q_u
      end if
    end if
  end for
  % At the end of time slot δt
  for each stationary sensor k in the area j do
    if missing_t ≥ 1 − REQ_Q_t then
      Report sensing reading to server
      Update overall sensing quality
    end if
  end for
end for
```

The server will also check the sensor readings to decide whether there is suspected unusual event in the network. If the sensing reading is outside the normal range, it will increase the sensing quality requirement REQ_Q_t to get more sensing data from the area. Although mobile phones can provide sensing data without consuming additional energy in the resource-limited stationary sensors, the mobility of mobile phone users are not controllable. Hence, it may lead to inadequate sensing data if there are not enough mobile phone users in the area. Stationary sensors can perform sensing as complementary to the mobile phones in order to achieve better overall sensing quality. If the sensing quality achieved by the mobile phones does not meet REQ_Q_t, stationary sensors will be enabled to perform sensing at the end of that time slot. Algorithm 1 shows the pseudo-code of the above implementation.

VI. Evaluations

A. Simulation Settings

We evaluate our adaptive collaborative sensing algorithm with the real mobile traces collected from the mobile phone participants in Disney World (Orlando) [21], [22]. The human mobility traces are collected with GPS receivers carried by 41 participants at every 10 seconds. These traces are mapped into a two dimensional area and recomputed to a position at every 30 seconds by averaging three samples over that 30 second period to account for GPS errors [21].

The simulation is conducted considering the sensing area of size 2000m x 2000m at the center of the amusement park.

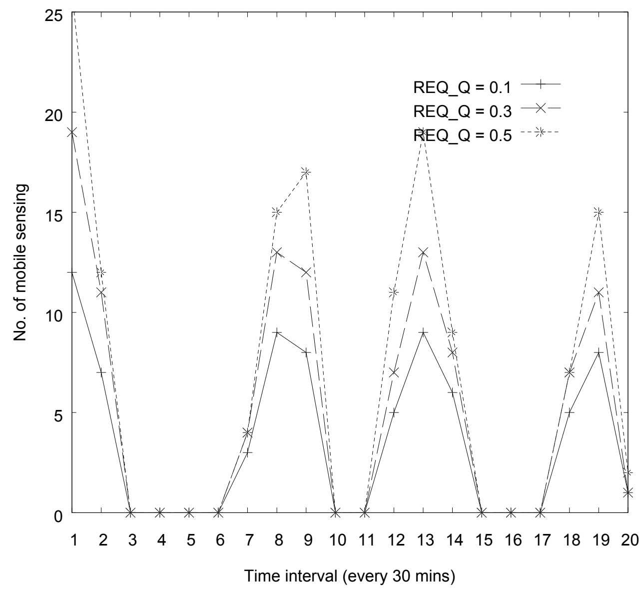

Fig. 2. Number of sensing performed by mobile phones in each time interval with REQ_Q=0.1, 0.3 and 0.5 respectively.

There are totally 25 stationary sensors uniformly deployed in the sensing field. We divide the sensing field into grid cells with size 50m x 50m each. The simulation time and mobile traces last for 10 hours. The stationary sensors and mobile phones can measure the noise levels and take pictures from the environment. We further divide the simulation time into time intervals with 30 minutes. We run our collaborative sensing algorithm for each grid cell every time interval. Both the mobile phones and stationary sensors follow the same sensing model as stated in Eq. 1.

B. Sensing in Normal Situation

In the first experiment, we measure the achieved sensing quality, the number of sensing performed by mobile phones and stationary sensors in each time interval. Normal situation without any unusual events is considered in the sensing field for this experiment. We also vary the required sensing quality REQ_Q_n as 0.1, 0.3, and 0.5 respectively.

Figure 2 shows the number of sensing performed by mobile phones in the sensing field along time. We observe that mobile phones are involved more actively in sensing when the required sensing quality REQ_Q_n increases. Figure 4 shows the corresponding number of enabled stationary sensors in each time interval. It is interesting to see that the number of stationary sensors decreases as the number of mobile sensing increases. It indicates that mobile phones can effectively decrease the number of active stationary sensors and reduce their energy consumption.

Figure 4 shows the average sensing quality of all grid cells obtained by both the mobile phone users and stationary sensors in the environment. We can see that the achieved sensing quality is higher when the REQ_Q increases. However, the sensing quality is not able to reach $REQ\_Q = 0.5$ even

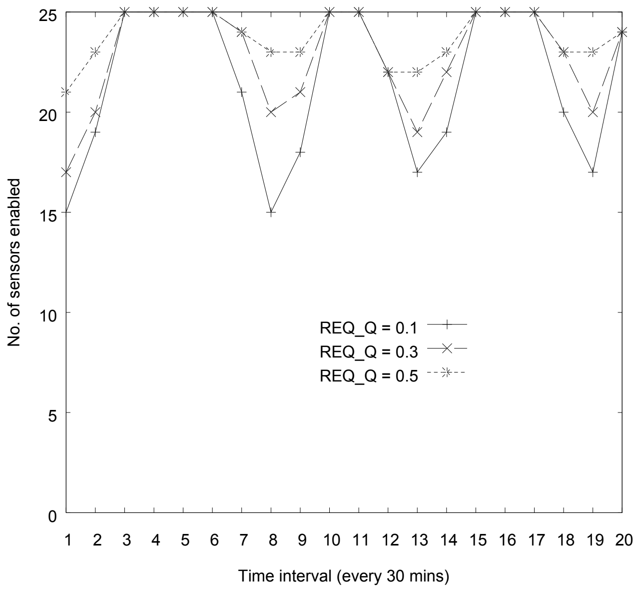

Fig. 3. Number of sensors enabled in each time interval with REQ_Q=0.1, 0.3 and 0.5 respectively.

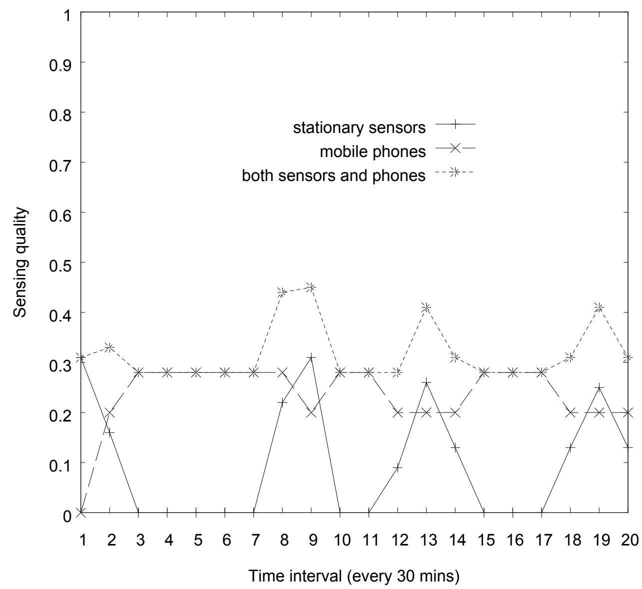

Fig. 5. Sensing quality achieved in grid cell (20, 15) in normal situation.

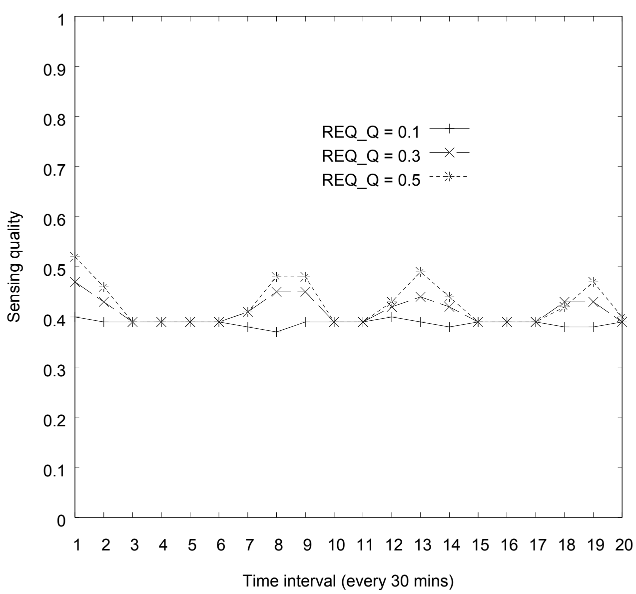

Fig. 4. Average sensing quality along time with REQ_Q=0.1, 0.3 and 0.5 respectively.

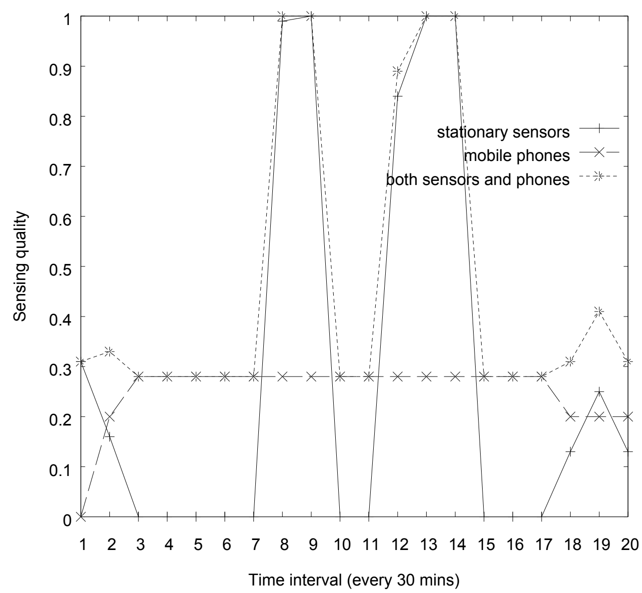

Fig. 6. Sensing quality achieved in grid cell (20, 15) with an unusual event occurred between time intervals 7 and 14.

though it is the target of the system. This is due to the inadequate number of mobile phone users available in the sensing field and the limited number of deployed sensors.

C. Adaptivity to Unusual Events

We aim at evaluating the adaptivity of our algorithm in response to the unusual event in this experiment. The required sensing quality in normal situation REQ_Q_n is set to 0.25, while that of the unusual event is set to $REQ\_Q_u = 0.7$. We consider an unusual event occurs in grid cell (20, 15) between time intervals 7 to 14, corresponding to the 210 to 420 minutes in the simulation time.

Figure 5 shows the sensing quality achieved by stationary sensors, mobile phones and both types of devices together at grid cell (20, 15) under normal situation. It demonstrates that the collaboration of both stationary sensors and mobile phones can effectively increase the overall sensing quality of the grid cell. Again, the higher sensing quality achieved by mobile phones, the less sensing quality is required to be provided by stationary sensors. Hence, more stationary sensors can save energy from not performing sensing and communication.

We then repeat the experiment in the case that unusual events occurred in the grid cell from time intervals 7 to 14. An unusual event could be an accident occurred in the amusement park, which may cause increased noise level and crowds of people. During an event period, we would expect the sensing quality of the system to be maximized to provide as much as information about the environment as possible. Figure 6 shows the sensing quality achieved by stationary sensors, mobile phones, and a combination of both of them. Obviously, the sensing quality increases dramatically from 0.3 to 1 when there is unusual event occurred at time interval 7. The mobile phone users report a lot of sensing data about the unusual events in emergency. Due to the limited number of stationary sensors, 0.3 is already the best sensing quality can be achieved by the system even though all stationary sensors are fully functioned. We observe that the sensing quality keeps very high during the occurrence of the unusual event, except in time intervals 10 and 11. The drop of the sensing quality is due to the lack of mobile phone users in the sensing field, so that all of the sensing can only be provided by the stationary sensors. As the time moves on, the sensing quality returns to normal in time interval 15 when there is no more unusual event in the area.

VII. Conclusions

In this paper, we proposed an adaptive collaborative sensing algorithm to coordinate the sensing activities among the mobile phones and stationary sensors in the sensing field. We suggested that mobile phones could be given higher priority in collaborative sensing, given their stronger computation power and regularly charged battery compared with stationary sensors. Based on availability and sensing quality of the mobile phones, stationary sensors are enabled to perform sensing adaptively to reach the required sensing quality. More stationary sensors will be enabled if the availability and sensing quality of mobile phones are insufficient. The overall sensing quality of the system is further improved according to the sensor readings and the unusual events in the environment. Higher sensing quality will be provided if there are unusual events in the sensing field. Simulation results demonstrated that our algorithm can coordinate mobile phones and stationary sensors effectively to reduce the number of sensing performed, while providing satisfactory overall sensing quality. The results also showed that our system can improve the sensing quality adaptively to the unusual events in the environment.

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