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Launching Efficient Participatory Sensing Campaign: A Smart Mobile Device-based Approach

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Participatory sensing is a promising sensing paradigm that enables collection, processing, dissemination and analysis of the phenomena of interest by ordinary citizens through their handheld sensing devices. Participatory sensing has huge potential in many applications, such as smart transportation and air quality monitoring. However, participants may submit low quality, misleading, inaccurate, or even malicious data if a participatory sensing campaign is not launched effectively. Therefore, it has become a significant issue to establish an efficient participatory sensing campaign for improving the data quality. This paper proposes a novel five-tier framework of participatory sensing and addresses several technical challenges in this proposed framework including: 1) optimized deployment of data collection points (DC-points); and 2) efficient recruitment strategy of participants. Toward this end, the deployment of DC-points is formulated as an optimization problem with maximum utilization of sensor and then a Wise-Dynamic DC-points Deployment (WD3) algorithm is designed for high quality sensing. Furthermore, to guarantee the reliable sensing data collection and communication, a trajectory-based strategy for participant recruitment is proposed to enable campaign organizers to identify well-suited participants for data sensing based on a joint consideration of temporal availability, trust and energy. Extensive experiments and performance analysis of the proposed framework and associated algorithms are conducted. The results demonstrate that the proposed algorithm can achieve a good sensing coverage with a smaller number of DC-points and the participants that is termed as social sensors, are easily selected to evaluate the feasibility and extensibility of the proposed recruitment strategies.

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1. INTRODUCTION

Participatory sensing is an emerging and promising sensing paradigm that relies on the voluntary cooperation of users equipped with embedded or integrated sensors. This

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new data collection method offers excellent opportunities to address large-scale society problems [Weinschrott et al. 2010; Kanhere 2011]. Participatory sensing relies on the participation of end users with mobile computing devices (*e.g.*, smartphones) to create interactive sensor networks that enable data gathering, analysis, and sharing [Ahmadi et al. 2010]. Participatory sensing applications have recently been developed and spanned in diverse domains ranging from pure information sharing [Gaonkar et al. 2008] to participatory environmental monitoring [Kotovirta et al. 2012], such as urban air and noise pollution [Zheng et al. 2013; Rana et al. 2010], to social network applications [Dong et al. 2008] as well as route and behavior planning [Reddy et al. 2010b; Eisenman et al. 2007].

Fig. 1 illustrates the architecture of a typical participatory sensing application. The sensing data can be collected by the phones of volunteers or participants recruited by participatory sensing campaign organizers. Then, these collected data are reported to a central server for processing using wireless data communications. After the data are processed and analysed on the server, the sensing results are presented in various forms, such as graphical representations or maps. Simultaneously, the results may be displayed locally on the participants' mobile phones or accessed by the organizers of participatory sensing campaign.

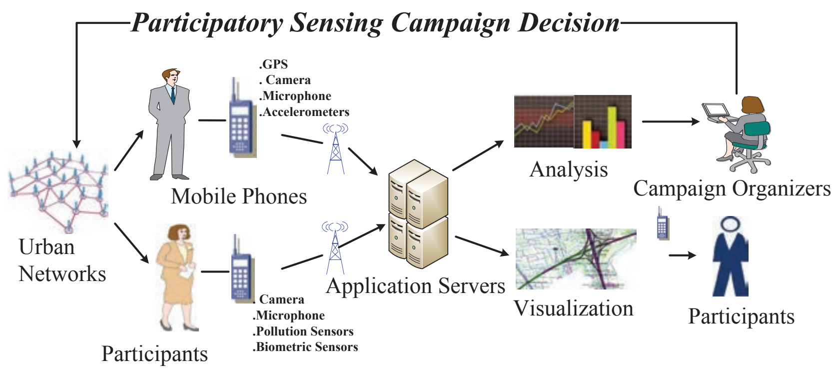


Fig. 1. Architectural Overview of a Typical Participatory Sensing Application

The major difference between participatory sensing and traditional sensing lies in the fact that each participant is regarded as a *"social sensor"*, sensing the surrounding environment to upload data. Thanks to participants' powerful ability for analysis and judgement, the Participatory Sensing Systems (PSSs) request the participants to sense the surrounding information dynamically. Therefore, it works timely and widely to reduce the burden on the system and enlarge the geographical coverage. However, participants as the data collection carriers are demanded to sense anytime and anywhere, which impede the wide use of participatory sensing. Furthermore, the participants are interested or related in the sensing campaign, and the number of participants is not large-scale, that just allow participatory sensing to be applied in a small range and variety diversity of projects.

Considering a real scenario of PM 2.5 real-time monitoring in Beijing City. In reality, there are insufficient air quality measurement stations in a city due to the expensive cost of building and maintaining such a station. For example, 35 air quality measurement stations are currently established in Beijing city. Since these stations are stationary base stations with the traditional network coverage mechanism, they cost lots of money and manpower. Generally, an air quality measurement station needs a certain size of land, huge amount of money (about 200,000 USD for construction and 30,000 USD per year for maintenance[Zheng et al. 2013]), human resources to regularly take care of it, and 24 hours per day power consumption. Thus, this fact greatly limits the number of measurement stations. However, we expect to obtain the measured values of air quality in PSSs through the mobile sensing devices held by crowd and further aggregate these values for intelligent services supply. In particular, the price of a handheld PM 2.5 sensing device powered by lithium battery (10 W) is 500 USD. At the worst case, the employers (e.g., environmental protection agency) buy devices for users who are willing to sense the air quality voluntarily/incentively. Roughly, 14,210 users can be recruited with the same cost consumed by the traditional sensing system every year for their participatory sensing campaign. From the sustainability point of view, the PS paradigm is better than the traditional sensing paradigm in terms of both cost and energy.

However, facilitating participatory sensing from a potential to a reality remains two major challenges. When a participatory sensing campaign is launched, the optimized deployment of DC-points should be handled with the aim of maximizing network coverage and minimizing sensing cost. Because participatory sensing is organized virtually, recruiting the particular participants for the campaign not only relies on participants' availability in the Point of Interest (POI), but also can be enhanced by incorporating participants' trust and energy of their sensing devices.

Motivated by the above statements and research challenges on participatory sensing, this paper makes the following major contributions:

— An original five-tier participatory sensing framework in PSSs is proposed. In this new framework, an optimized deployment scheme of the data collection points is investigated firstly in the deployment layer with consideration of maximum network coverage and energy-efficiency. Secondly, the social sensors are dynamically selected in the recruitment layer. Finally, the social sensors voluntarily/incentively sense their surrounding environment in the sensing layer.
— Based on the analysis of static and dynamic deployment schemes in the proposed framework, a Wise-Dynamic DC-points Deployment (WD3) algorithm that incorporates the advantages of both schemes, is proposed. This algorithm with the considerations of the impact from the hot spot regions, is presented to deploy the data collection points for high quality sensing.
— In order to guarantee a high quality sensing by selecting the appropriate participants, a trajectory-based recruitment strategy of participants which considers the availability, trust and energy of users is proposed. In particular, the future trajectory of users are predicted by using Dynamic Tensor Analysis (DTA) algorithm. A basic selection strategy of participants is firstly devised in terms of availability. Further, a refined selection strategy of participants is discussed based on joint consideration of trust and energy of users.
— We present a case study of noise monitoring at a university campus to evaluate the feasibility and effectiveness of the proposed recruitment strategy. The experimental results show that the proposed WD3 algorithm can lead to the use of few DC-points that are able to cover the most part of the monitoring area in the deployment layer. Furthermore, the feasibility and effectiveness of our selection strategies of social sensors are evaluated in the recruitment layer.

The rest of this paper is organized as follows. Section 2 overviews the related work on DC-points deployment and participants recruitment in PSSs. The proposed framework and the problem statement of participatory sensing are presented in Section 3. Section 4 presents a Wise-Dynamic DC-points Deployment (WD3) algorithm to efficiently deploy the DC-points for high quality sensing. Section 5 is devoted to handling the recruitment strategy of participants based on their trajectory. Experimental results are shown in Section 6. Finally, Section 7 concludes this paper.

2. RELATED WORK

This section discusses the related research focusing on the deployment of DC-points and the issues of participants recruitment in PSSs, respectively.

2.1. DC-Points Deployment

In participatory sensing, the issue of deploying data collection points deployment has not been addressed in prior work. Most existing studies on participatory sensing have assumed that the data collection points are initially given without any optimizations, such as sensing coverage maximization and deployment cost. Generally, an optimal scheme aims to achieve sensing coverage as large as possible by deploying the number of collection points as small as possible. From this point of view, this research issue is related to the sensing coverage problem in sensor networks [Li et al. 2013; Wang 2011]. In sensor networks, the coverage problem reflects how well a sensor filled is monitored and it is one of the most important performance metrics to measure sensor networks. The existing approaches on coverage problem in sensor networks mainly focus on energy conservation and lifetime optimization due to limited resources of sensor networks. The approach proposed in [Osmani et al. 2009] aims to maximize coverage while minimizing sensor movement. Their results demonstrate that the proposed method does achieve good coverage with the less movement for adjusting the deployment but it does require a complex algorithm running in the sensor nodes. [Wang et al. 2006] presented three separate deployment protocols to support a high level of coverage with minimal movement in a short time. However, the scalability of the protocols suffers some problems. [Ammari and Das 2012] proposed configuration protocols to solve the problem of k-coverage in wireless sensor networks and proved that their protocols select a minimum number of sensors to achieve full k-coverage of a field while guaranteeing connectivity between them. Recently, the artificial intelligence algorithms are widely used for sensor deployment issue. By using artificial bee colony algorithm, [Mini et al. 2014] identifies optimal deployment locations of the given sensor nodes with a pre-specified sensing range, and schedules them for a maximum network lifetime with the required coverage level. [Liao et al. 2015] targets at achieving full coverage of the monitoring area and prolonging network lifetime, an ant colony optimization algorithm based sensor deployment scheme is proposed. Instead of selecting and placing static devices to maximize coverage, our work differs in that the participants recruitment process is carried out after determining the “visual” data collection points. Besides, DC-points deployment in our paper does not need to take the energy factor into account at this stage. Importantly, our proposed deployment scheme can obtain the maximized sensing coverage with the considerations of hot spots and obstacles.

2.2. Participants Recruitment

The process of identifying suitable participants is usually performed with associated considerations, such as availability, reputation, expertise, and trust. In most PSSs, availability of participants in terms of geographic and temporal coverage of the sensing area is critical. For example, in an air quality sensing campaign of a university campus, it is desirable to recruit participants who regularly pass through the sensing region and cover as much of the area as possible. [Reddy et al. 2010a] pioneered the study on a recruitment framework for participatory sensing systems which aims at identifying suitable participants based on parameters such as geographical and temporal availability of participant. Incorporating the distributed computing, [Tuncay et al.

2012] proposed a distributed recruitment framework of participants for opportunistic sensing. The recruitment component exploits the suitability of user behaviours, and based on the mobility history information, recruits only the nodes that are likely to be in the sensing area when the sensing activity is taking place. The reputation-based, expertise-based as well as trust-based recruitment schemas are also widely studied in PSSs. Recently, a trust-based participants recruitment framework for PSSs is proposed in [Amintoosi and Kanhere 2013b]. Their framework leverages multi-hop friendship relations to identify and select suitable and trustworthy participants among friends or friends of friends, and finds the most trustable paths to them. Further, they proposed an application-agnostic reputation framework for social PSSs by considering both the quality of contribution and the trustworthiness level of participant within the social network [Amintoosi and Kanhere 2013a]. In addition, [Wang et al. 2013] solved a problem of two conflicted objectives “anonymity” and “trust” in PSSs. To this end, a privacy-preserving provenance model, a data trust assessment scheme and an anonymous reputation management protocol are investigated. Our previous work [Hao et al. 2014] presents a framework of participatory sensing and then develops a trajectory-based recruitment strategy of social sensors in order to enable service providers to identify well suited participants for data sensing based on temporal availability, trust, and energy. [Luo et al. 2014] designs an incentive mechanism based on all-pay auctions for selecting the social sensors in participatory sensing, this proposed approach accommodates incomplete information with information asymmetry, risk-averse agents and stochastic population. In [Karaliopoulos et al. 2015], the researchers formulate the selection of users as a minimum cost set cover problem with a submodular objective function and put forward a practical greedy heuristic algorithm for the solving the users selection problem. Different from the existing participants recruitment methods, the strategy proposed in this paper is based on tensor which can represent and process the multi-dimensional data efficiently. Specifically, the novelty of our recruitment strategy takes the mobility, trust, and energy of mobile users into account together in order to grantee the reliable sensing data.

3. FRAMEWORK FOR PARTICIPATORY SENSING SYSTEMS

This section firstly presents a novel framework of PSSs and exhibits two key challenges about DC-points deployment as well as social sensors recruitment. Then, a problem of participatory sensing campaign launching is provided.

3.1. The Proposed Five-tier Framework

Fig. 2 presents a new five-tier framework for PSSs proposed in this paper. The framework is composed of five layers (namely, data collection points deployment layer, participants recruitment layer, data sensing layer, data transmission layer, and data processing layer) in which different functionalities are enabled. We elaborate the functions and responsibilities of each layer by a bottom-up view approach.

(1) ***Data Collection Points Deployment Layer:*** This layer determines an optimized deployment scheme of the data collection points in a given monitoring area. Intuitively, an optimized deployment scheme of the data collection points implies an efficient and accurate participatory sensing campaign. Generally, the deployment scheme based on maximum sensing coverage is taken into account.

(2) ***Participants Recruitment Layer:*** Considering the limited budget and dynamical behaviors of users, a dynamic recruitment strategy of social sensors need to be proposed in this layer. The main factors that affects recruitment of social sensors are as follows: 1) the availability of users in pre-deployed data collection points; 2) trust value of users; 3) the remaining power of their mobile phones. To recruit

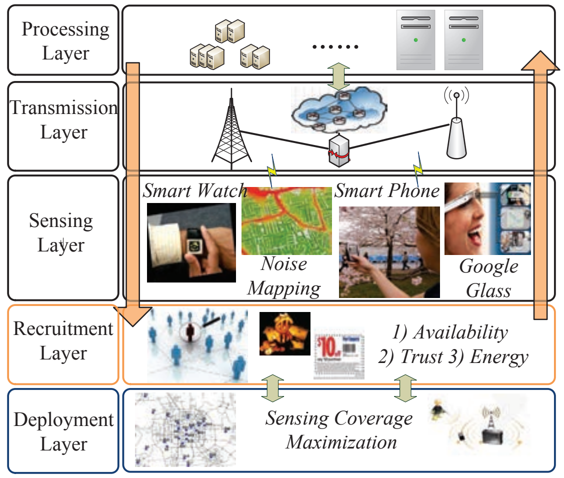


Fig. 2. Five-tier Participatory Sensing Framework.

the targeted users as the social sensors, some necessary incentivations, such as awarding gifts and coupon are adopted.

(3) ***Sensing Layer:*** This layer is devoted to sensing the surrounding environment using sensors that are embedded in the mobile phones, smart watches, Google glasses, etc. Once users move to or approach the pre-deployed data collection points, the incentive mechanisms will be initiated to request them for sensing the surrounding environmental context.

(4) ***Data Transmission Layer:*** To provide reliable data transmission services, data transmission layer manages the transmission of obtained sensing data to the data center for further processing by the Internet. Before accessing the Internet, mobile users may send the sensing data via either WLANs or Cellular networks. From the energy-saving point of view, there exists an important issue about heterogeneous wireless networks selection.

(5) ***Data Processing Layer:*** Servers analyze and process the received sensing data including data aggregation, redundant data filtering, as well as data mining and so on [Jara et al. 2010]. By processing the obtained sensing data, some relevant services can be provided, such as early warning of traffic jam and climate forecast.

As can be seen from Fig. 2, there exists a reciprocal relationship between the processing layer and the social sensors recruitment layer. The processing layer not only aggregates and analyzes the collected sensing data but also estimates the trust and energy during their multiple participatory sensing interactions. It will directly affect the recruitment strategy in the recruitment layer.

3.2. Key Challenges and Problem Statement

The essence of participatory sensing is data collection and interpretation. Participation requirements allow a campaign organizer (data analyst) to recruit and encourage participants that have a certain level of experience or are available in a certain time-spatial space. The key challenges of the PS campaign are to determine the optimized deployment of data collections points (DC-points) and design efficient recruitment strategy in which each participant can be dynamically selected and assigned to a set of DC-points where data should be collected. In this section, we formally describe this problem incorporated with the aforementioned two challenges as follows.

(**Participatory Sensing Campaign Launching**) Given a $R \times R$ area and a group of participants with their mobile traces, the entire PS campaign determination is composed of the following two technical aspects:

(1) Detecting the data collection points (DC-points) which can maximize the network coverage of the given area in the deployment layer.
(2) For a campaign $C(G, T)$, where G as the set of grids including the DC-points, and T represents the set of time of data sensing and collection determined by the campaign requirements. Thus, the recruitment problem in the recruitment layer is to dynamically select each participant $u \in U$ (U is the set of users) to any DC-point located in G, such that DC-point in a grid g is closer to the location of u than to that of any other participant in U.

Then, those recruited participants will carry out $C(G, T)$ at required time and location for campaign organizers. Clearly, the proposed research problems fall into the deployment layer and recruitment layer as shown in Fig. 2. Sections 4 and 5 will discuss how to deploy the data collection points as well as how to recruit the participants based on their trajectory in PSSs.

4. A WISE-DYNAMIC DC-POINTS DEPLOYMENT SCHEME

Aiming to detect the optimized DC-points deployment scheme in the given $R \times R$ area, we firstly analyse the static and dynamic deployment schemes: 1) Hexagon-based GAF-Like DC-points static deployment algorithm; and 2) Virtual Force based DC-points dynamic deployment algorithm. Based on the detailed analysis and discussion on the above static and dynamic deployment algorithms, a wise dynamic DC-points deployment scheme and its corresponding algorithm are presented. The DC-points deployment can be formulated as an optimization problem of utilization of sensor. The objective is to maximize the utilization of sensor η. In other words, maximizing η is equivalent to maximizing the sensing coverage A and minimizing the number of DC-points D for saving the cost of participatory sensing campaign. Formally, this optimization problem is mathematically described as follows,

$$\max \ \eta = \frac{A}{D * \pi r_i^2}$$
$$s.t. \quad A = R^2 \bigcap \{\bigcup_{i=1}^{D} a_i\}.$$

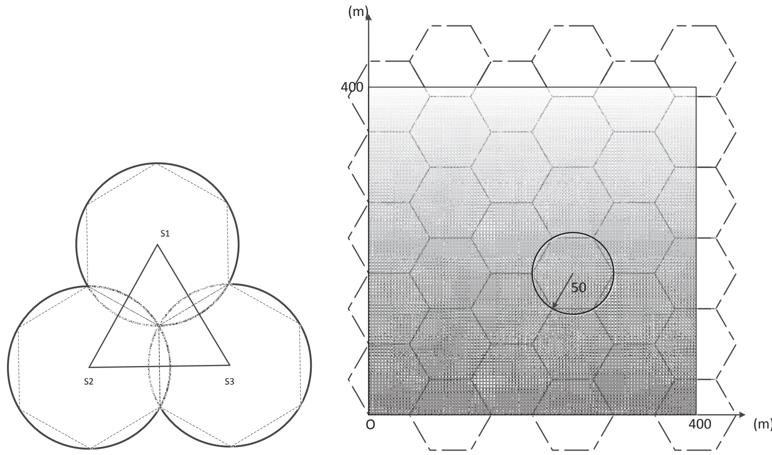
where r_i and a_i indicate the sensing radius and coverage of sensor s_i, respectively.

4.1. Static Deployment

For the static deployment of DC-points, a Hexagon-based GAF-like algorithm [Xu et al. 2001] was utilized to obtain a seamless coverage deployment solution for the given monitoring area. This approach, as shown in Fig. 3(a), ensures that all the points in this area are fully covered at the cost of more sensors to be used. In a 400×400 m^2 monitoring area as illustrated in our experiment, 33 hexagon cells are required to cover the whole area as shown in Fig. 3(b).

The hexagon-based GAF-like algorithm guarantees 100 % network coverage if at least 33 sensors operate in the active mode in each round, one for each cell. Obviously, the sensor utilization, η, of this deployment solution can be calculated as

$$\eta = \frac{400^2}{33 * \pi 50^2} = 0.617 \tag{1}$$



(a) Hexagon coverage

(b) 33 hexagons are required to cover a $400 \times 400m^2$ area

Fig. 3. Static Deployment of DC-points

4.2. Dynamic Deployment

Since the number of participants is not considerably large in real-life participatory sensing campaign, a dynamic deployment of DC-points is urgently needed and used to minimize the number of DC-points and improve the sensor utilization, η.

The dynamic deployment algorithm consists of two technical steps: 1) computing virtual force interacted with DC-points and 2) adjusting the positions of DC-points according to the resultant force calculated by all virtual force interacted on them.

4.2.1. Virtual Force Computation. The basic idea of virtual force algorithm (VFA) [Zou and Chakrabarty 2004] is that the sensor field of wireless sensor network can be regarded as a potential field and each sensor behaves as a “source of force” for all other sensors. This force can be either positive (attractive) or negative (repulsive).

Definition 4.1. (**Virtual Force of a Sensor**) Let $\overrightarrow{F}_i$ be a resultant virtual force determined by the vector sum of all the forces acting on the sensor s_i, it is formulated as follows,

$$\overrightarrow{F}_i = \sum_{j=1,j\neq i}^{k} \overrightarrow{F}_{ij} + \overrightarrow{F}_{iR} + \overrightarrow{F}_{iA} \tag{2}$$

where $\overrightarrow{F}_{ij}$ refers to the virtual force between s_i and s_j; $\overrightarrow{F}_{iR}$ indicates the virtual repulsive force between sensors and obstacles, such as buildings; and $\overrightarrow{F}_{iA}$ denotes the virtual attractive force between sensors and coverage areas. Fig. 4 depicts a stress analysis diagram of sensor s_1 with Hot Spot Region and Obstacle. For a real-life sensing environment, Hot Spot Regions and Obstacles are usually exist in the sensing environment. Since we pay more attention to the Hot Spot regions rather than obstacles, thus more participants are hopefully recruited for further sensing in Hot Spot regions while fewer participants are recruited for sensing nearby obstacles. Clearly, the resultant virtual force of s_1 is calculated with $\overrightarrow{F}_1 = \sum_{j=1,j\neq i}^{4} \overrightarrow{F}_{1j} + \overrightarrow{F}_{1R} + \overrightarrow{F}_{1A}$.

Let d_{th} be the threshold on the distance between sensor nodes, and r be the sensing radius. Then, $\overrightarrow{F}_{ij}$ is calculated by using the following equation,

$$\overrightarrow{F}_{ij} = \begin{cases} (\omega_A(d_{ij} - d_{th}), \alpha_{ij}) & \text{if} \quad d_{ij} > d_{th} \\ 0 & \text{if} \quad d_{ij} = d_{th} \\ (\omega_R \frac{1}{d_{ij}}, \alpha_{ij} + \pi) & \text{if} \quad d_{ij} < d_{th} \end{cases} \tag{3}$$

where d_{ij} is the Euclidean distance between s_i and s_j, ω_A and ω_R denote the constant coefficients of virtual attractive force and virtual repulsive force, and α_{ij} is the orientation (angle) of vector from s_i to s_j.

Since the computational approaches [Zou and Chakrabarty 2004] of $\overrightarrow{F}_{iR}$ and $\overrightarrow{F}_{iA}$ are similar to that of $\overrightarrow{F}_{ij}$, this paper will not unfold elaboration of their computation.

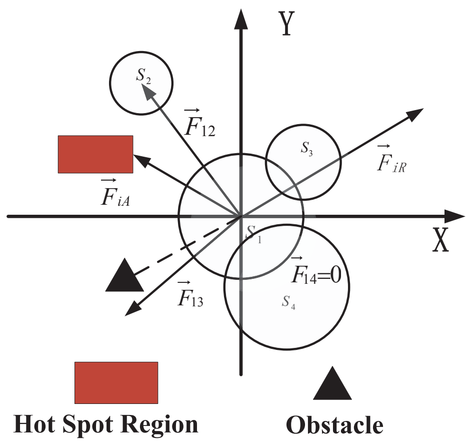


Fig. 4. The Stress Analysis Diagram of Sensor s_1

4.2.2. Performance Analysis. To better understand the working process and advantages of VFA, the simulation experiments are conducted in the same monitoring area $400 \times 400\ m^2$ including 28 sensors. Fig. 5(a) shows an initial random deployment in the monitoring area. Then, this initial deployment is optimized by using VFA and a final deployment of these sensors is obtained as shown in Fig. 5(b). Apparently, the sensing coverage in Fig. 5(b) is almost filling in the most region of the area. As can be seen from Fig. 5(c), the coverage ratio is changing from 75 % at the beginning stage to 97 % due to multiple VFA iterated operations.

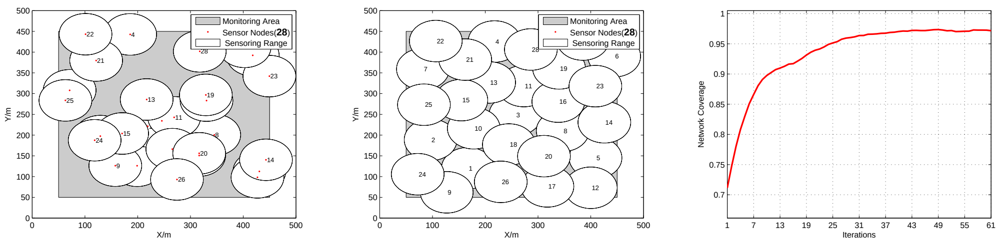
Likewise, the utilization of sensor η of this dynamic deployment solution can be calculated as

$$\eta = \frac{400^2 * 0.97}{28 * \pi 50^2} = 0.706 \tag{4}$$

Obviously, the sensor utilization, η, in the dynamic deployment solution is larger than that of the static one, and the number of sensors is also reduced. Both of them are playing an important role in participatory sensing campaign, hence, the dynamic deployment solution is preferred.

4.3. WD3 Algorithm

In real-life participatory sensing, we need to consider the Hot Spot Regions for high quality sensing campaigns. This section presents an enhanced dynamic deployment



(a) Initial deployment (b) Final deployment (c) Network coverage

Fig. 5. Dynamic Deployment of DC-points

algorithm, namely Wise-Dynamic DC-points Deployment (WD3) algorithm, which integrates the benefits of the existing Hexagon-based GAF-like static deployment algorithm and VFA. Therefore, WD3 algorithm has the following unique features:

— WD3 algorithm inherits the advantages of Hexagon-based GAF-like static deployment algorithm, thus, it can realize the better seamless sensing coverage.
— WD3 algorithm inherits the advantages of FVA algorithm, thus, it also considers the practical requirements for Hot Spot Regions and obstacle.
— Based on the above inherited advantages, WD3 algorithm has a relative high sensor utilization.

4.3.1. Algorithm Description. The proposed WD3 algorithm, as shown in Algorithm 1, works as follows: The algorithm aims to obtain an optimized deployment scheme with relatively high sensor utilization, η, within the monitoring area including Hot Spot Regions $\mathbf{H}$, and Sensor $\mathbf{S}$ as the input data. First, Hexagon-based GAF-like static deployment algorithm is applied to each region h_i for achieving the maximum seamless coverage c_i of $\mathbf{H}$. Additionally, the centroid (x, y) and radius r' of the coverage c_i are calculated. Then, WD3 evaluates the probability of coverage c_{xy} of each point (x, y) dominated by each sensor s_i. If c_{xy} is greater than a given threshold, then the point (x, y) is covered by s_i. Otherwise, the Hot Spot Region Coverage c_i is viewed as a new "*virtual sensor*", then WD3 employs VFA to adjust the positions of these sensors in order to cover the given area as much as possible.

4.3.2. Performance Analysis of WD3 Algorithm. To evaluate the performance of the proposed WD3 algorithm, the Hot Spot Regions are taken into account in the same monitoring area. An initial random deployment in the area without Hot Spot Regions, as shown in Fig. 6(a), is optimized using WD3 algorithm. Fig. 6(b) depicts an optimized deployment of DC-points with 30 sensors and 96 % coverage ratio.

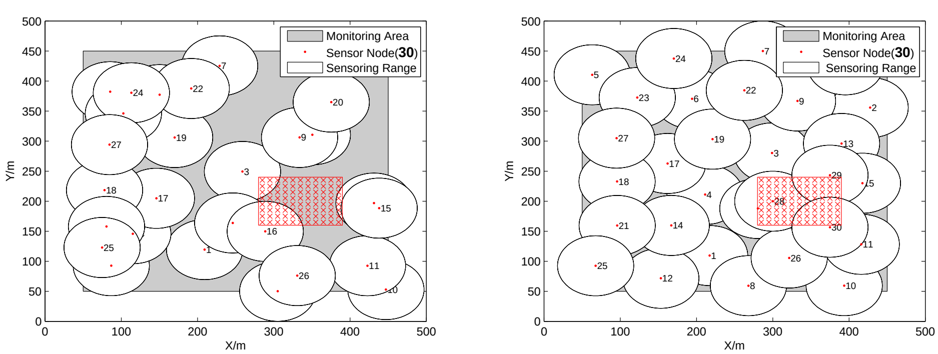
Therefore, the sensor utilization, η, of this WD3 deployment scheme can be calculated as

$$\eta = \frac{400^2 * 0.96}{30 * \pi 50^2} = 0.652 \quad (5)$$

It is clear that, the proposed WD3 deployment algorithm outperforms the Hexagon-based GAF-like algorithm in terms of utilization of sensor. Moreover, the proposed algorithm considers the practical requirements for Hot Spot Regions in PSSs and can achieve the seamless coverage better than VFA algorithm.

ALGORITHM 1: WD3: A Wise-Dynamic DC-points Deployment Algorithm

Data: Monitoring Area ($width \times height$), Hot Spot Regions $\mathbf{H} = \{h_1, \cdots, h_n\}$, Sensors $\mathbf{S} = \{s_1, s_2, \cdots, s_k\}$
Result: An Optimized Deployment of DC-points
begin
  for $h_i \in \mathbf{H}$ **do**
    Cover the region h_i by Hexagon GAF-like Algorithm;
    Find the Centroid (x, y) and radius r' of the Coverage c_i;
  end
  Set $loop = 0$
  Set $Max = \mathbf{MAX}$
  for $loop < Max$ **do**
    for *any point* $(x, y) \in MonitoringArea, x \in [1, width], y \in [1, height]$ **do**
      for $s_i \in \mathbf{S}$ **do**
        $c_{xy} \leftarrow (s_i, (x, y))$
      end
      if *coverage requirements are met* **then**
        Break from the Loop;
      end
    end
    /* Regard Hot Spot Region Coverage c_i as a "*Virtual*" sensor */
    for $s_i \in \boldsymbol{S}$ **do**
      $\overrightarrow{F}_{ij} \leftarrow (r, \omega_A, \omega_R, d_{th}, d_{ij})$
      $\overrightarrow{F}_{iC} \leftarrow (r, r', \omega_A, d_{iC})$
      $\overrightarrow{F}_{iR} \leftarrow (\omega_{negR}, d_{th}, d_{iR})$
      $\overrightarrow{F}_i = \sum_{j=1, j\neq i}^{k} \overrightarrow{F}_{ij} + \overrightarrow{F}_{iR} + \overrightarrow{F}_{iC}, j \in [1, k], j \neq i$
    end
    for $s_i \in s_1, s_2, \cdots, s_k$ **do**
      $\overrightarrow{F}_i$ virtually moves s_i to its next position
    end
    Set $loop = loop + 1$
  end
end



(a) Initial deployment (b) Final deployment

Fig. 6. The Deployment of DC-points based on WD3 Algorithm

5. A TRAJECTORY-BASED RECRUITMENT STRATEGY OF PARTICIPANTS

This section presents a trajectory-based recruitment strategy of participants. By predicting the trajectory data of participants, it can help us to select the appropriate participants for joining the participatory sensing campaign. At first, an overview of the selection strategy is provided. With this strategy, the trajectory data tensorization, collection, training, and prediction are then elaborated in detail, respectively.

5.1. Overview of the Strategy

The proposed recruitment strategy of participants works within a given monitoring area with M grids and N users. As shown in Fig. 7, the recruitment strategy of participants contains the following five steps:

Step 1. **Trajectory Data Tensorization**: The trajectory data of users associated with users, time and location is represented by a tensor $\chi \in \Re^{I_t \times I_g \times I_u}$.
Step 2. **Sampling Data Collection**: The trajectory data is collected within i days. The trajectory data in the i^{th} day is a tensor χ_i. Therefore, the collected data is represented by a time-series tensor $\chi^T = \{\chi_1, \chi_2, \cdots, \chi_i\}$.
Step 3. **Training**: The time-series tensor χ^T is trained by using Dynamic Tensor Analysis (DTA) approach [Sun et al. 2006]. Then, an approximate tensor $\widetilde{\chi}$ is obtained.
Step 4. **Tensor-based Prediction**: Based on the obtained approximate tensor, the user's future moving patterns/expected arrived locations are predicted.
Step 5. **Social Sensors Selection**: At each time, we dynamically select the optimal social sensors who can satisfy the availability, trust and energy constraints. According to the historical trajectory, we infer the availability of each social sensor appearing in the targeted grid by the approximate tensor. During the interaction of participatory sensing, the trust and energy of each social sensor are taken into account timely for adjusting the selection results. Then, the selected social sensors are stimulated to participate in a given sensing campaign.

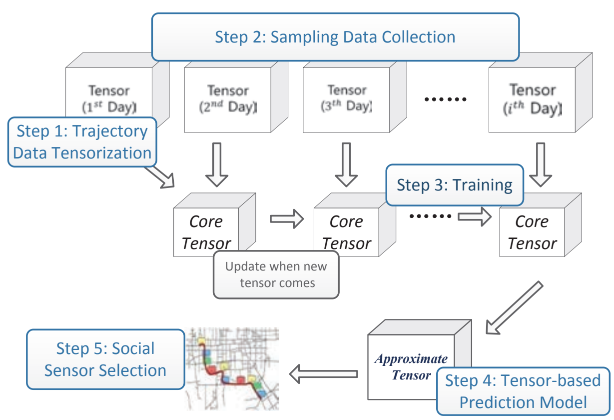


Fig. 7. The overview of our recruitment strategy of social sensors

With this overview of our proposed recruitment strategy of participants, the following sections present the detailed strategy with tensor based DTA algorithm. A tensor, as a type of high dimension matrix which governs the correlations among these dimensions is widely used in many applications [Kolda and Bader 2009]. In PSSs, the trajectory data of a certain period is regarded as a type of high-dimensional tensor which is associated with users, time, and location. These dimensions constructed as a tensor are important for representation, processing and storage of PSSs. Hence, this strategy can help us to discover the potential semantic relationships from those data and provide intelligent services for the participatory sensing campaign.

5.2. Trajectory Data Tensorization and Collection

In a given monitoring area, there are N users who are doing their daily activities. In order to tensorize the trajectory data of these N users, we first partition this area with M grids, and then collect the daily GPS trajectory data with k time intervals. As depicted in the Figure 8 on a two dimensional plane, we can sequentially connect these GPS points into a curve based on their GPS log. Each point corresponds a latitude and longitude which can falls into a certain grid.

	Latitude	Longitude	Time
P1	Lat1	Lngt1	T1
P2	Lat2	Lngt2	T2
......	......	......	......
Pk	Latk	Lngtk	Tk

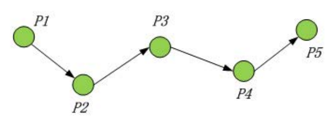


Fig. 8. GPS Log and GPS Trajectory for One User

Due to the multiple users participation in the PSSs, the trajectory data generating from PSSs is apparently mainly composed of three dimensions: *users*, *time*, *locations* (Note that the longitude and altitude of a certain location corresponds to a certain pre-partitioned grid). Element of the daily trajectory data can be described as a 4-tuple $a =< T, G, U, V >$ where T is time, G refers to the grid where the user is staying, U denotes a certain user, and V is the element's value. This 4-tuple corresponds to a 3-order tensor as follows:

$$\chi \in \Re^{I_t \times I_g \times I_u}, \tag{6}$$

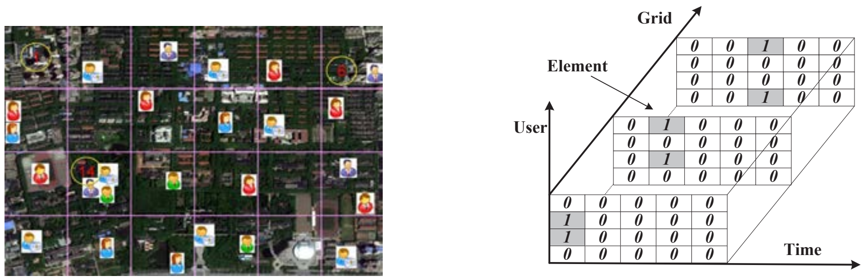
where $\Re$ is defined on the real number domain. I_t, I_g, and I_u refer to time, location grids, and users. $I_t \times I_g \times I_u$ denotes the Cartesisan product of each individual domain. The value of each element $x(t_k, g_m, u_n)$ in the 3-order tensor represents the likeness of user u_n is staying at grid g_m at time t_k which is obtained by GPS-enabled devices. For example, if user u_3's location falls into grid g_2 at time t_1, then $x(t_1, g_2, u_3) = 1$.

In other words, a user can only belong to one grid at a certain time. Hence, the constructed tensor as shown in Fig. 9(b) including the daily trajectory data is very sparse.

Before the trajectory data training, we construct the time-series tensor $\chi^T = \{\chi_1, \chi_2, \cdots, \chi_i\}$ by collecting the daily trajectory data of users during i days.

5.3. Trajectory Data Training

Dynamic Tensor Analysis (DTA) is an efficient algorithm for dynamically revealing the hidden correlations among the dimensions (e.g., time, users, and locations in PSSs) of



(a) Monitoring Area with Grids

(b) Tensor Representation for Trajectory

Fig. 9. Trajectory Data Tensorization.

the tensor. Therefore, we adopt DTA algorithm to analyze the time-series tensor χ^T and mine the potential trajectory patterns of users in PSSs.

An initial tensor can be matricized in several modes which are determined by their order. For example, the tensor $\chi \in \Re^{I_t \times I_g \times I_u}$ has three unfolding matrices, $X_{(1)}^{I_t \times I_g I_u}$, $X_{(2)}^{I_g \times I_t I_u}$ and $X_{(3)}^{I_u \times I_t I_g}$. Each unfolding matrix $X_{(d)}$ of corresponding mode d can be decomposed into a projection matrix $U_{(d)}$ and an energy matrix $S_{(d)}$ via Singular Value Decomposition (SVD) [Sun et al. 2008]. Then, a covariance matrix $C_{(d)}$ can be calculated by

$$C_{(d)} = U_{(d)} S_{(d)} U_{(d)}^T. \quad (7)$$

The DTA algorithm processes each mode of the tensor continuously. Importantly, $C_{(d)}$ is updated as follows,

$$C_{(d)} \leftarrow \lambda C_{(d)} + X_{(d)} X_{(d)}^T, \quad (8)$$

where $\lambda \in [0, 1]$ is a forgetting factor regarded as the predictable information aggregator of time-series data. In other words, the recent timestamps are more important than those far in the past.

The updated covariance matrix $C_{(d)}$ is further decomposed into a matrix $U'_{(d)}$ and an energy matrix $S'_{(d)}$. To reduce noisy data, we select top $r_{(d)}$ eigenvectors among matrix $C_{(d)}$ and induce a new corresponding projection matrix $U_{(d)}$ which is used for the calculation of core tensor. In addition, it is also stored to calculate $C_{(d)}$ of the next time-series tensor.

Using the above method, we can obtain all three mode projection matrices $U_{(1)}$, $U_{(2)}$ and $U_{(3)}$. The Core tensor ε is obtained by,

$$\varepsilon = \chi \times U_{(1)}^T \times U_{(2)}^T \times U_{(3)}^T, \quad (9)$$

This core tensor ε has a special block-diagonal structure whose elements indicate the level of interactions between time, users and locations.

The aforementioned method for calculating the core is just a training process focused on one time stamp. Clearly, the core ε in the time-series tensor χ^T is updating dynamically. The calculation of the core is equivalent to learning the historical tensors.

Then, an approximate tensor, $\widetilde{\chi}$, eventually used in tensor-based prediction model is obtained according to the above core ε, as follows,

$$\tilde{\chi} = \varepsilon \times U'_{(1)} \times U'_{(2)} \times U'_{(3)}. \quad (10)$$

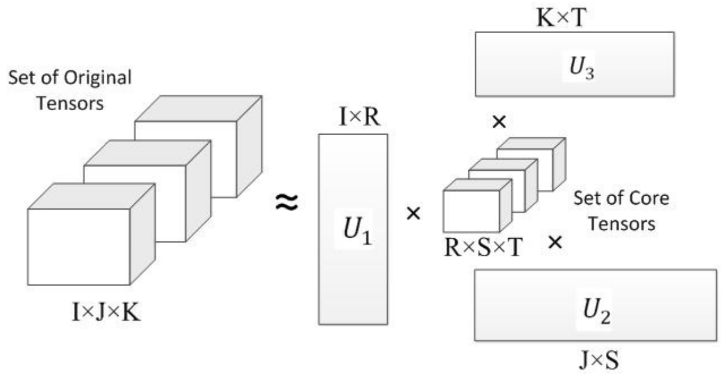


Fig. 10. The process of offline tensor analysis

Based on the above theoretical analysis of the conventional DTA algorithm, Algorithm 2 presents an efficient DTA-based model for training time-series tensor that is constructed from the trajectory data in PSSs.

ALGORITHM 2: DTA-based Time-series Tensor χ^T Training

Data: Time-series Tensor χ^T, old projection matrices $U_{(d)}$, energy matrices $S_{(d)}$, output ranks $r_{(d)}$, $(d \in [1, 2, 3])$, forget factor λ
Result: Approximate Tensor $\widetilde{\chi}$
begin
  Set $i = 1$
  for $i \leq$ **DAYS do**
    For each $\chi_i \in \chi^T$
    Unfolding χ_i as three matrices $X_{(d)}$
    for $d = 1$ *to* 3 **do**
      For each $X_{(d)}$ do SVD operation
      $(U_{(d)}, S_{(d)}) \leftarrow SVD(X_{(d)})$
      $C_{(d)} = U_{(d)} S_{(d)} U_{(d)}^T$
      Set $U_{(d)}$ be the top $r_{(d)}$ eigenvectors of $C_{(d)}$
      $C_{(d)} \leftarrow \lambda C_{(d)} + X_{(d)} X_{(d)}^T$
    end
    /* core tensor ε is updating day by day. */
    $\varepsilon = \chi \times U_{(1)}^T \times U_{(2)}^T \times U_{(3)}^T$
    $i = i + 1$
  end
  $\tilde{\chi} = \varepsilon \times U'_{(1)} \times U'_{(2)} \times U'_{(3)}$
end

To better illustrate the advantages of the proposed algorithm, we compared the DTA algorithm with offline tensor analysis algorithm in terms of time and space complexity.

Offline tensor analysis differs from the DTA approach. It is a high dimensional tensor analysis approach which is derived from principle component analysis (PCA) algorithm. For example, for a given 3-order time-series tensor $\{\chi_1, \chi_2, \cdots, \chi_i\}$. The working process of offline tensor analysis is shown in Fig. 10.

(1) Firstly, we make the Decomposition for each matrix unfolding and calculate the middle variable Z_i for each tensor χ_i. $Z_i = \chi_i \times U^{(1)T} \times \cdots, U^{(d-1)T} \times \cdots, U^{(d+1)T} \times \cdots, U^{(M)T}$. Clearly, if the size of time-series tensor is n, the time complexity equals $\Theta(Mn^3)$.
(2) Then, we update the covariance matrix $C_{(d)}$, s.t $C_{(d)} = C_{(d)} + Z_{(d)} Z_{(d)}^T$. Obviously, the singular value matrix can be easily obtained from $C_{(d)}$. Then, we select the top $r_{(d)}$ value and set $U^{(d)}$ as the corrsponding singular value vector. The time complexity of this process is $\Theta(n^3)$.
(3) Finally, the core tensors of all tensors are calculated, i.e., $\varepsilon_i = \chi_i \times U^{(1)T} \times \cdots, U^{(d-1)T} \times \cdots, U^{(d+1)T} \times \cdots, U^{(M)T}$. And its time complexity equals $\Theta(Mn^3)$.

Suppose there are k M-order original tensors defined on n dimensions. The time and space complexity of offline tensor analysis and DTA algorithms are compared in Table. I.

Table I. Comparison of time and space complexity

Algorithm \ Complexity	Time Complexity	Space Complexity
Offline Tensor Analysis	$\Theta(kM^2n^3)$	$\Theta(kMn^3)$
Dynamic Tensor Analysis	$\Theta(kMn^3)$	$\Theta(n^M)$

According to the comparison results of time and space complexity, it is clearly to find that DTA algorithm can efficiently reduce the store capacity of data. In addition, the space complexity of DTA algorithm is greatly less than offline tensor analysis. This unique feature of DTA algorithm is playing important role in big data era. Note that, the time complexity of DTA algorithm is less than the offline tensor analysis algorithm, and the former one fully takes into account the dynamic updating of data. While offline tensor analysis is lack of flexibility, and not efficiently meets the service requirements of participatory sensing.

5.4. Trajectory Prediction and Social Sensors Selection

The approximate tensor $\widetilde{\chi} \in \Re^{I_t \times I_g \times I_u}$ is actually an information aggregator of the results learned from the previous time-series tensors. Each element value in $\widetilde{\chi}$ denotes the likeness of a certain user who appears in a certain grid at a certain time. Therefore, the future trajectory can be predicted by the approximate tensor.

Since there are some users to be selected for the settled time and the grid, we propose a select-strategy to pick up the better volunteers. At each time, we can dynamically select the optimal social sensors who can satisfy the availability, trust and energy constraints. For example, the availability can be predicted by the approximate tensor. We rank the likeness value of the users in the descending order, and choose the top-k users who may be the potential social sensors. Based on this idea, the following two strategies: *1) basic selection strategy; 2) refined selection strategy* are devised as shown in Fig. 11.

5.4.1. Basic selection strategy. As a basic selection strategy, the availability is a critical factor to be considered. The selection process of the top-K social sensors based on this strategy is formulated as follows,

$$U(t_k, g_m, K) := \arg \max_{u_{a_i} \in u_n}^{K} \tilde{x}(t_k, g_m, u_n) \tag{11}$$

For a targeted grid g_m at time t_k, the availability based selection strategy of social sensors is dependent on the likeness rank of the users appearing in the targeted area at that time, *i.e,*

$$\tilde{x}(t_k, g_m, u_{a_1}) > \tilde{x}(t_k, g_m, u_{a_2}) > \tilde{x}(t_k, g_m, u_{a_3})... \tag{12}$$

Apparently, users u_{a_1}, u_{a_2} and u_{a_3} are selected as the top-3 social sensors in this case.

5.4.2. Refined selection strategy. To improve the sensing data reliability, the energy and trust factors are jointly taken into account, then a refined selection strategy is devised. On one hand, if a social sensor candidate u in the top-k social sensors list has already participated and been selected in the sensing campaign more frequently (for example, h times of participation), it implies that u has a high trust value $Trust(u) = f(h)$, here $f(.)$ is a trust function associated with participation times. Then, we extract the social sensors whose trust value are greater than a given threshold δ. On the other hand, the service providers wish the possible social sensors have the enough energy/power $Energy(u)$ remained in their mobile devices. The energy consumption for each participant during the sensing follows an exponential decay trend [Miettinen and Nurminen 2010] $E(t) = E(0)e^{-2t}$, where $E(t)$ indicates the residual energy at time t, $E(0)$ is an initial energy in their mobile devices. Thus, each social sensor should report back the remaining energy information and sensing data, and similarly another given threshold θ is adopted for further refining in order to guarantee the continuous and reliable data sensing and communication. The refined selection strategy is formulated as follows,

$$U'(t_k, g_m, K) := \arg \max_{u_{a_i} \in u_n}^{K} \tilde{x}(t_k, g_m, u_n)$$

$$s.t. \quad \begin{cases} Trust(u_i) \geq \delta \\ Energy(u_i) \geq \theta \end{cases}$$

where $u_{a_i}(i \in [1, k])$ belongs to the top-K social sensors list and the parameters δ, θ are determined by service providers.

In fact, putting the constraints in the refined selection strategy $U'(t_k, g_m, K)$ is equivalent to re-ranking the selected social sensors using basic selection strategy $U(t_k, g_m, K)$ according to a critical evaluation metric $\psi(u_n)$ that is associated with two affecting factors *Trust* and *Energy*, *i.e,*

$$\psi(u_n) = \beta Trust(u_n) + (1 - \beta) Energy(u_n) \tag{13}$$

where $\beta \in [0, 1]$ is a weight parameter for balancing those two factors. In other words, the selected top-k social sensors will be re-ranked in terms of $\psi(u_n)$.

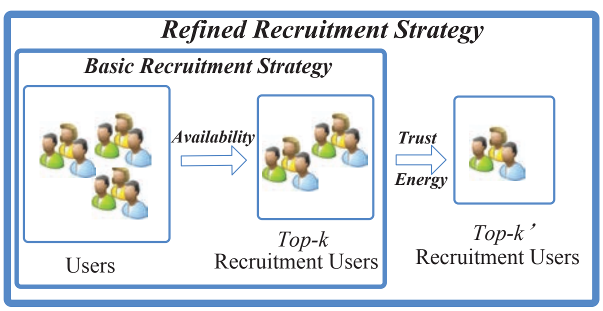


Fig. 11. Two Selection Strategies of Social Sensors

6. CASE STUDY

In this section, we present two typical cases of participatory sensing at the campuses of Huazhong University of Science and Technology (HUST) and Northwestern Polytechnical University (NWPU) in China, respectively. The reasons why we choose the HUST and NWPU as the places for participatory sensing are as follows: 1) the road networks in these two campuses are shaped with many grids; 2) the number of participants are enough for an efficient participatory sensing campaign; 3) the mobility patterns are relative stable during the sampling period. First of all, an optimized deployment of DC-points is conducted with the proposed WD3 algorithm. Then, a basic recruitment strategy is evaluated from the aspects of feasibility and effectiveness.

6.1. Setup of Participatory Sensing Campaign

6.1.1. Setup of HUST campus. For a given monitoring area, we firstly partition it into 20 grids. Without loss of generality, we set 2 grids, say g_4 and g_{19} as the Hot Spot Regions in our participatory sensing campaign. In the PS data set, we have collected the GPS location and noise information every 2 minutes between 8:00-8:40 AM from a number of volunteers at the university from September to November, 2013. Thus, these collected daily trajectory data can be constructed as a 3-order tensor which includes users, grids, and time dimensions. The detailed steps can be found at our open website[1].

6.1.2. Setup of NWPU campus. Similar with the setup of HUST campus, we also partition the given monitoring area into 25 (i.e.,5×5) grids. There are 23 students from different departments participating in our experiment. We have collected the GPS location and noise information every 15 seconds between 7:00AM-11:00 PM from these volunteers for one week. Thus, these collected daily trajectory data can be also constructed as a 3-order tensor which includes users, grids, and time dimensions.

6.2. Results and Discussions

In our participatory sensing campaign, Fig. 12 shows that the DC-points are deployed in five grids g_4, g_7, g_{13}, g_{19} and g_{20} of the HUST campus by using WD3 algorithm. Importantly, these five girds can maximize the utilization of sensor. Likewise, the obtained grids in NWPU campus can maximize the utilization of sensor. The results for two campuses are presented as follows, respectively.

6.2.1. Results of HUST Campus. After data collection, the time-series tensor χ^T of trajectory data is trained by DTA algorithm. For the purpose of illustration and visualization, we choose the trajectory data gathered by 5 typical volunteers between 2 Nov and 8 Nov 2013 as shown in Fig. 13(a). Table II shows the expected participants to be recruited at four different times in five grids including pre-deployed DC-points. Clearly, the campaign organizer will recruit users u_1, u_4 as the potential social sensors in grid g_4 at time t_7. The likeliness value reflects the possibility of users who are to be recruited. However, user u_5 in orange will not be considered in this participatory campaign due to his low likeliness. For example, user u_4 should be first considered as a social sensor in grid g_4 at time t_6 because of the higher likeliness value compared to that of u_1.

As mentioned previously, trust as one of the considerations in the refined selection strategy, is an important personalized factor [Amintoosi and Kanhere 2013b]. Thus, we pay attention to the reachable grids of an individual user as shown in Fig. 13(b). Obviously, u_1 is more likely available in grid g_{13} which includes pre-deployed DC-points

[1]http://epic.hust.edu.cn/ps

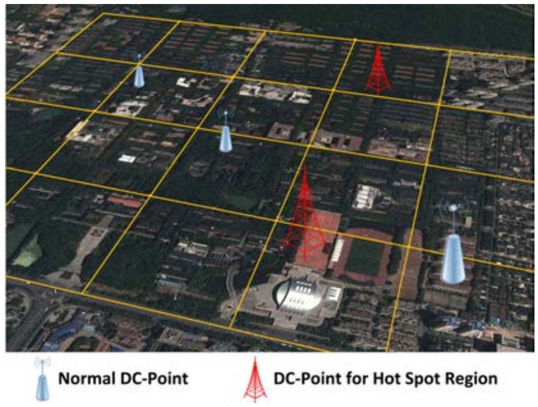
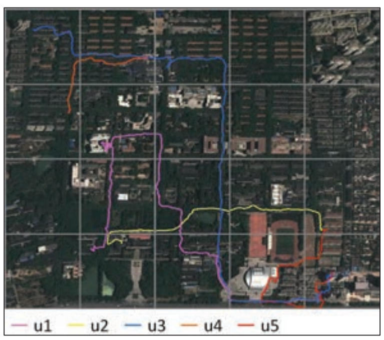
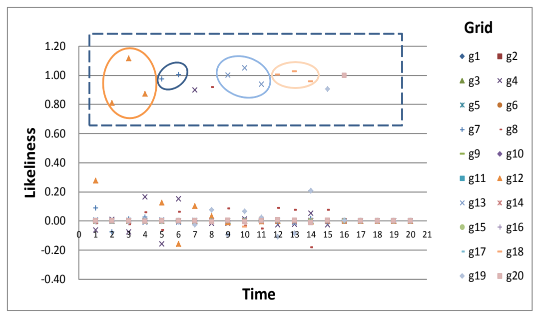


Fig. 12. The Deployment of DC-points in HUST campus



(a) Trajectory of five typical volunteers on 5 NOV



(b) Trajectory Distribution in terms of Grids for a Certain User u_1

Fig. 13. Visualization of Trajectory and Its Distribution for a Certain User

Table II. Expected Participants to be Recruited using Basic Selection Strategy in Various PS Campaigns

Campaign $C < grid, time >$	Participants user (likeliness)
$C < g_4, t_6 >$	u_4 (0.963), u_1 (0.152),u_3 (0.017)
$C < g_4, t_7 >$	u_4 (1.036), u_1 (0.901), u_5 (0.036)
$C < g_7, t_5 >$	u_1 (0.977), u_2 (0.001)
$C < g_{13}, t_{10} >$	u_1 (1.052), u_3 (-0.102)
$C < g_{13}, t_{11} >$	u_1 (0.938)
$C < g_{19}, t_{10} >$	u_5 (1.131), u_2 (-0.230)
$C < g_{19}, t_{11} >$	u_5 (0.958)
$C < g_{19}, t_{14} >$	u_5 (0.230), u_1 (0.210)
$C < g_{20}, t_{15} >$	u_5 (1.118)

from time t_9 to t_{11}. If we choose u_1 as the social sensor at that period, more interactions are benefit to enhancing the trust value that may assist the further selection next time. We also analyze the statistics on trust and energy of potential social sensors u_1 and u_4 in Table III. For example, u_1 has been recruited in campaign $C< g_7, t_5 >$, therefore, his trust value is increased from 0.5 to 0.6. As the time elapses, his residual energy is also reduced from 0.65 to 0.6.

Table III. Statistics on Trust and Energy of Expected Participants to be Recruited using Refined Selection Strategy in Various PS Campaigns

Campaign	Participants		
	user (likeliness)	user(trust)	user(energy)
$C < g_7, t_5 >$	u_1 (0.977)	Trust(u_1)=0.5	Energy(u_1)=0.65
$C < g_4, t_6 >$	u_4 (0.963)	Trust(u_4)=0.3	Energy(u_4)=0.8
$C < g_4, t_7 >$	u_4 (1.036), u_1 (0.901)	Trust(u_1)=0.6, Trust(u_4)=0.4	Energy(u_1)=0.6, Energy(u_4)=0.76

Table IV. Expected Participants to be Recruited using Refined Selection Strategy with Different β in Various PS Campaigns

Campaign	Participants ($\psi(u_n) = \beta Trust(u_n) + (1-\beta) Energy(u_n)$)		
	β=1	β=0	β=0.5
$C < g_7, t_5 >$	$\psi(u_1)$ =0.5	$\psi(u_1)$ =0.65	$\psi(u_1)$ =0.575
$C < g_4, t_6 >$	$\psi(u_4)$ =0.3	$\psi(u_4)$ =0.8	$\psi(u_4)$ =0.55
$C < g_4, t_7 >$	$\psi(u_1)$ =0.6, $\psi(u_4)$ =0.4	$\psi(u_1)$ =0.6, $\psi(u_4)$ =0.76	$\psi(u_1)$ =0.6, $\psi(u_4)$ =0.58

Table IV presents the recruitment results of social sensors using refined selection strategy with different β in various PS campaigns. As can be seen from Table IV, the expected participants are re-ranked with the various considerations: 1) β=1, trust factor is only considered, 2) β=0, energy factor is only considered, and 3) β=0.5, both factors are taken into account upon the basic selection strategy.

6.2.2. Results of NWPU Campus. Similar with the above analysis, the time-series tensor T of trajectory data is trained by DTA algorithm once the data are collected. Table V shows the expected participants to be recruited for multiple participatory sensing campaigns. Due to the limited space of this paper, the sensing time are compressed into some time slots, such as $t_{2631} - t_{2638}$ indicates a time slot from t_{2631} to t_{2638}. Note

Table V. Expected Participants to be Recruited using Basic Selection Strategy in Various PS Campaigns

Campaign $C < grid, time >$	Participants user (likeliness)
$C < g_7, t_{271} - t_{278} >$	u_1, u_6,u_{14}
$C < g_7, t_{317} - t_{336} >$	u_1, u_8, u_7
$C < g_7, t_{2631} - t_{2638} >$	u_6, u_3 , u_{20}
$C < g_7, t_{2729} - t_{2736} >$	u_6, u_{10} , u_{14}
$C < g_7, t_{3053} - t_{3573} >$	u_6, u_9 , u_{22}
$C < g_{17}, t_{252} - t_{257} >$	u_1
$C < g_{17}, t_{1882} - t_{1893} >$	u_2, u_4,u_{16}

that, the participatory sensing campaign during the time slots from t_{271} to t_{278} and t_{317} to t_{336}, user u_1 is definitely selected as a social sensor. Similarly, user u_6 as a social sensor can execute the participatory sensing at three time slots $t_{2631} - t_{2638}$, $t_{2729} - t_{2736}$ as well as $t_{3053} - t_{3573}$ in grid g_7. Besides, for a series of continuous participatory sensing campaigns $C < g_{17}, t_{252} - t_{257} >$ and $C < g_{17}, t_{1882} - t_{1893} >$, different users are selected as the social sensors.

Based on the above results, it is obvious to conclude that our proposed efficient trajectory-based social sensor selection strategy has a good scalability and extensibility. That is to say, our selection strategy can also cope with the participatory sensing campaign case inclduing many users at different grids within a long-term sensing period.

7. CONCLUSIONS

To realize a sustainable sensing, this paper investigates a novel approach for launching an efficient participatory sensing campaign. We first present a five-tier framework of PSSs and illustrate two main challenges of DC-points deployment and social sensors recruitment and their importance in PSSs. A wise-dynamic DC-points deployment (WD3) scheme and its corresponding algorithm are proposed in the deployment layer and applied for a purposeful recruitment of social sensors in the recruitment layer. Further, a trajectory-based recruitment strategy of social sensors is devised for participatory sensing. Specifically, the collected trajectory data of users within a period are constructed as a 3-order time-series tensor. Then, DTA algorithm is adopted to train this time-series tensor and predict the future trajectory that supports the basic selection strategy based on availability. In addition, a refined selection strategy of social sensors is proposed with the joint consideration of trust and energy of participants. Finally, the proposed selection strategies are evaluated via a practical case study conducted at two university campuses. The proposed framework and associated techniques are expected for achieving intelligent services in PSSs by the virtue of the participatory power of the selected well-suited participants.

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