Sociability-Driven User Recruitment in Mobile Crowdsensing Internet of Things Platforms

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***Abstract*—The Internet of Things (IoT) paradigm makes the Internet more pervasive, interconnecting objects of everyday life, and is a promising solution for the development of next-generation services. Smart cities exploit the most advanced information technologies to improve and add value to existing public services. Applying the IoT paradigm to smart cities is fundamental to build sustainable Information and Communication Technology (ICT) platforms. Having citizens involved in the process through mobile crowdsensing (MCS) techniques unleashes potential benefits as MCS augments the capabilities of the platform without additional costs. Recruitment of participants is a key challenge when MCS systems assign sensing tasks to the users. Proper recruitment both minimizes the cost and maximizes the return, such as the number and the accuracy of accomplished tasks. In this paper, we propose a novel user recruitment policy for data acquisition in mobile crowdsensing systems. The policy can be employed in two modes, namely sociability-driven mode and distance-based mode. Sociability stands for the willingness of users in contributing to sensing tasks. Performance evaluation, conducted in a real urban environment for a large number of participants, reveals the effectiveness of sociability-driven user recruitment as the average number of recruited users improves by at least a factor of two.**

I. Introduction

The Internet of Things (IoT) paradigm envisions everyday life objects to be “smart”, to communicate with each other and with the users and to enable pervasive and ubiquitous computing [1]. IoT devices are uniquely identifiable and are equipped with communications, computing and sensing capabilities. Taking advantage of the variety and the potentially enormous volume of the data generated by these devices will foster the development of innovative applications in a broad range of domains. Applying the IoT paradigm to urban scenarios is of special interest to support the smart cities vision [2], [3]. Smart cities aim at using ICT solutions to improve the quality of life of citizens by provisioning innovative solutions for public services such as healthcare, public safety and smart transportation among others [2], [4]. The IoT paradigm is the candidate building block to develop sustainable ICT platforms for smart cities. Including citizens in the loop with crowdsensing approaches augments capabilities of existing infrastructures without additional costs and is proved to be a win-win strategy for urban applications [5].

Mobile crowdsensing (MCS) has emerged in the recent years, becoming an appealing paradigm for sensing data. In MCS, users contribute data generated from sensors embedded in mobile IoT devices such as smartphones, tablets and wearables. The aggregated information is then delivered to a collector [6]. The pervasive diffusion of smartphones and wearables along with the rich set of built-in sensors in these devices, are the primary enablers leading to the success of MCS paradigm. Accelerometer, gyroscope, GPS, microphone and camera are only a representative set of sensors that have facilitated the development of a number of applications in a wide range of scenarios, including health care, environmental and traffic monitoring and management [7].

Data acquisition in MCS can be either *participatory* or *opportunistic* [7]. In opportunistic sensing systems, the user involvement is minimal: sensing decisions are application- or device-driven. In participatory sensing systems, users are actively engaged in the sensing process. The users are recruited by a central platform, which dispatches sensing tasks. Users can decide which request to accept and, upon acceptance, they have to accomplish the tasks by sensing and reporting data. From one point of view, opportunistic sensing systems lower the burden to user participation as devices or applications are responsible to take sensing decisions. Conversely, participatory sensing systems are tailored to crowdsensing architectures with a “central platform”, which facilitates system control operations such as task assignment and rewarding to compensate user contribution. Participatory systems can also mitigate some of the privacy concerns about enabling opportunistic data collection.

One of the key challenges in MCS is user recruitment. In urban environments, the high number of potential contributors calls for the design of efficient recruitment policies. Proper policies allow selection of well-suited users able to fulfill sensing tasks with high accuracy while minimizing the system costs. Such costs have a double nature. On one hand, the central platform organizes and dispatches tasks and thus sustains a monetary cost to recruit and reward users for their contribution. On the other hand, users also sustain costs for their contributions such as spending energy from batteries for sensing and eventually using their data subscription plan for reporting.

In this paper, we define a novel user recruitment policy for data acquisition in MCS systems for smart cities. The proposed policy leverages two criteria, i) user sociability,

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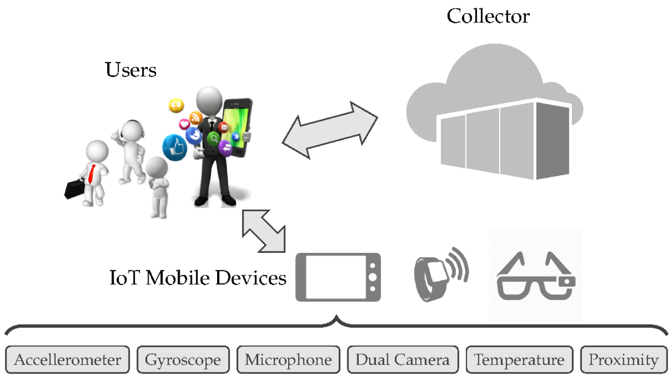


Figure 1. System scenario

which is an estimate of the willingness of users to participate in and contribute to sensing tasks, and ii) the spatial distance between users and tasks. The policy can be employed in two modes: the social-driven recruitment mode (SDRM) and the distance-based recruitment mode (DBRM). The latter assigns sensing tasks to the users on the sole basis of their distance to the location of the task. The former also includes user sociability during the selection process. Highly sociable users share many interests with friends and are more active, i.e., they are constantly using their devices online, which makes them excellent candidates for data acquisition. We evaluate the performance of SDRM via simulations in a real urban environment and with a large number of participants. Through simulations, we have shown that sociability-driven user recruitment improves the average number of recruited users by at least a factor of two. Moreover, SDRM always outperforms DBRM in terms of number of accomplished tasks. Even in the extreme case of complete failure of DBRM, SDRM can successfully accomplish 10% of the tasks.

The rest of the paper is organized as follows. Section II presents background on MCS and motivates the need for social-based recruitment policies. Section III details the proposed methodologies for user recruitment. Section IV provides performance evaluation and Section V concludes the work and outlines future research directions on the topic.

II. Background and Motivation

MCS data acquisition platforms are systems in which users contribute information from IoT mobile devices. Such information is then delivered to a collector, typically located in the cloud, to be at disposal of the organizer of the sensing campaign for processing and analysis. Fig. 1 illustrates the main elements of a typical MCS system.

To organize a MCS campaign, the organizer, such as a government agency, an academic institution or business corporation, sustains costs to recruit and compensate users for their involvement. Therefore, devising a proper recruitment policy is essential. On one hand, it allows the organizer to minimize the expenditure. On the other hand, it helps to choose those users that will successfully carry out the campaign. For example, in the public safety context, selecting users to maximize the trustworthiness in data acquisition is critical [8], [9].

Several research efforts investigate task assignment and user recruitment in MCS systems, also called participant selection. The majority of the proposed policies aim at minimizing the sensing cost for the organizer while guaranteeing a certain level of system accuracy, such as coverage of the sensing area [10], [11], [12], [13]. Reddy et al. [10] propose a recruitment policy which selects the participants on the basis of their availability in collecting data in a given geographical area and at a defined time. In the context of opportunistic sensing systems, Karaliopoulos et al. formulate an optimization problem for cost minimization and predict user location with deterministic and stochastic mobility models [11]. With the objective of minimizing energy consumption to report sensed data, piggyback crowdsensing techniques can be employed [12], [13]. More precisely, piggyback crowdsensing leverages users' phone call and other application usage to upload gathered information [14]. The authors of [12] propose three greedy algorithms to find the minimum number of participants to guarantee a minimum coverage level, whereas the authors of [13] exploit historical records to predict user call and thus determining coverage of sensing area. He et al. [15] not only propose an efficient algorithm for time-dependent assignment of tasks, but they also devise a novel pricing mechanism to reward users based on bargaining theory. Unlike the aforementioned works, Liu et al. [16] propose an energy-efficient participant selection scheme, which relates the residual battery charge of the users to their willingness to contribute. The scheme ensures the quality of sensed information in terms of the amount of collected data per task.

The closest work to our study exploits social relationships to establish a trusted route between service requester and provider parties [17]. More specifically, the service requester is interested in acquiring information on a given phenomenon. If the service provider belongs to the same community of the requester, it receives the sensing task. Otherwise, the task is offered to users belonging to overlapping communities until it reaches the service provider. Social ties between the users within each community guarantee the trust of the passage of task offers among communities.

Given the state of the art, in this paper, we investigate the impact of user sociability on task recruitment. Sociable users are more active and use their devices online intensively [18]. As a result, they are excellent candidates for data acquisition. Moreover, the majority of existing works only consider the cost that the platform/organizer to compensate/reward users for their contribution, but do not capture the cost for recruitment itself.

III. User Recruitment Policy

Recruitment policies define the criteria for user eligibility to contribute to crowdsensing campaigns. The proposed policy exploits user sociability and the distance between the users and the sensing task as selection criteria. Table I lists description of symbols used to define the user recruitment policy.

The platform/organizer of the crowdsensing campaign $\mathcal{C}$ is interested in acquiring data from given *points of interest* in the

Table I
SYMBOLS LIST AND DESCRIPTION

SYMBOL	DESCRIPTION
$\mathcal{C}$	Crowdsensing campaign
w	Task w
$\mathcal{W}$	Set of tasks $\mid w \in \mathcal{W}$
u	User u
$\mathcal{U}$	Set of users $\mid u \in \mathcal{U}$
t	Duration of a single task t
T	Duration of the sensing campaign
l	Location of users and tasks
$d_{u,w}$	Distance (m) between user u and task w
D_{max}	Maximum distance between eligible users
p	Popularity factor associated to each location
s	Sociability factor associated to each user
a	Task acceptance factor
N	Minimum number of users to mark a task as *accomplished*
C	Set of coordinates <*latitude, longitude, altitude*> of city layout

city, also called the *sensing terrain*. The organizer defines a set of sensing tasks $\mathcal{W} = \{w_1, w_2, \ldots, w_W\}$ and each task w_i is described by its location l_i and time duration t_i, i.e. $w_i(l_i, t_i)$. The location l is defined in terms of latitude and longitude and the time duration t is given in timeslots. As a result, the duration T of the campaign $\mathcal{C}$ is as follows:

$$T = \sum_{i \in \mathcal{W}} t_i. \tag{1}$$

Let $\mathcal{U} = \{u_1, u_2, \ldots, u_U\}$ be the set of users potentially employed to accomplish the tasks. Each user u_i is described in terms of their current location and sociability factor, i.e. $u_i(l_i, s_i)$. It is worthwhile mentioning that both user location and sociability factor are time dependent and s_i can assume real values in $[0, 1]$. Practically, user sociability can be defined in terms of the amount of data users consume or the time they spend using mobile social network applications, or their combination [19]. Sociability is an essential parameter to consider for user recruitment. Users with high sociability are more active and use their devices online intensively, which makes them excellent candidates during the selection process. Moreover, they tend to visit more places and get connected to more users, which further increases their mobile social activity [18].

To assess sociability, it is necessary to determine the data usage or the total time that a user spends on a particular social network application in a single session. Once acquired, the instantaneous values are averaged by the number of sessions in a time window, e.g., an hour or a day. The actual user sociability is then determined through the Exponential Weighted Moving Average filter (EWMA) over the values obtained in each time window. This allows tuning and eventually limits the contribution of older values. It is worth mentioning that the sociability metric determined with this method is a relative metric based on a normalized value of user's sociability by the maximum sociability value in the network.

During each timeslot, the recruitment policy selects users with highest *recruitment factor* r from the set $\mathcal{U}$. For each user i, the *recruitment factor* is defined as follows:

$$r_i = \alpha \cdot \frac{1}{d_{u_i, w_j}} + (1 - \alpha) \cdot s_i; \tag{2}$$

where d_{u_i,w_j} is the distance between the location of user i and sensing task w_j, $j \in \mathcal{W}$. The Haversine formula can be employed to compute d_{u_i,w_j} [20]. Users located farther than D_{max} from the location of a sensing tasks are not considered eligible for being selected for the corresponding sensing task. Indeed, the closer the users are to the sensing task location, the higher the accuracy in capturing the phenomenon is. The parameter α is a balancing coefficient which can take a real value in $[0, 1]$. Having set $\alpha = 1$, the recruitment is agnostic of the sociability factor and we define this mode as *distance-based recruitment mode* (DBRM). Otherwise, it operates in *sociability-driven recruitment mode* (SDRM).

To recruit users, the campaign organizer sustains a cost. For each request sent to the users, the cost c associated to the task w is equal to 1 unit of cost. For example, the costs could be financial or expressed in terms of the bandwidth used to broadcast recruitment messages. The objective of the organizer is to minimize the total cost sustained while maximizing the number of task accomplished. The tradeoff between the recruitment cost and the number of accomplished tasks defines the efficiency of the recruitment policy.

Users can decide whether to accept or refuse the task. Acceptance is based on user sociability. Users with high sociability factor s are more likely to accept the task. The acceptance factor a is modelled as a logarithmically increasing function:

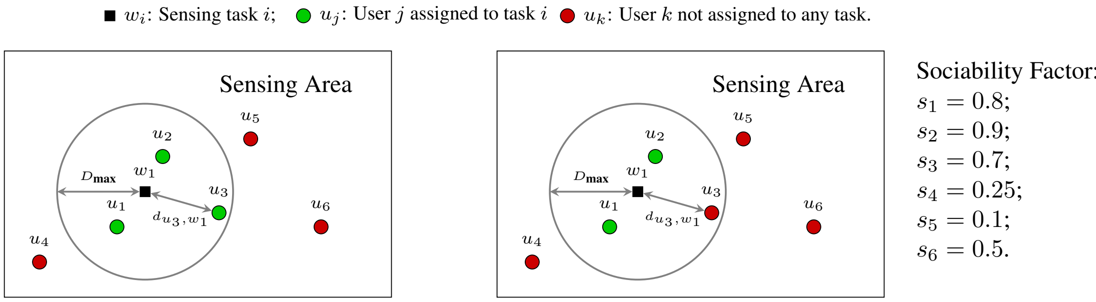
$$a = \log(1 + s). \tag{3}$$

The logarithmic description of the relation between a and s allows us to perform a fine-grain comparison of the task acceptance probability of users with low versus high sociability ratings. For high sociability users, the acceptance factor a will assume a value very close to 1. For low sociability users, a small difference between two sociability factors s_1 and s_2 will correspond to a considerable difference in the respective acceptance factors a_1 and a_2.

Upon acceptance, users contribute as long as they remain within a distance closer than D_{max}. In such a case, they are not contacted to contribute to the same task any longer. Moreover, a user refusing participation in a current timeslot will always be contacted in subsequent timeslots if the user is eligible for selection.

System-level accuracy increases if the organizer does not recruit persistently the same group of users to accomplish a task [21]. For this reason, each task w acquires the status *accomplished* if, during t, a given number N of individual users are involved and contribute by reporting data. During t_i, whenever it is not possible to recruit a sufficient number of users, the task i is marked as *failed*.

Like in social networks, some locations in cities are *hubs*, i.e., they attract a large number of individuals, whereas others do not [22]. To capture this phenomenon, each location l is assigned a popularity factor p, and p can take real values in



(a) SDRM (b) DBRM

Figure 2. User recruitment in social-driven and distance-based modes

the range $[0, 1]$. Practically, tasks associated to locations with high popularity factor should require a high number of users to successfully complete the task. In addition to the location popularity, also the time dimension plays a crucial role in defining N. Longer tasks require higher number of users than short ones to guarantee good levels of accuracy. As a result, the number of users N_i necessary to accomplish the task i out of U is calculated as shown in Eq. (4).

$$N_i = p_i \cdot (t_i/T) \cdot U. \tag{4}$$

Fig. 2 shows an example of user recruitment with the two modes, SDRM and DBRM. Three users, namely u_1, u_2 and u_3, are within the maximum distance radius D_{max}. Given all users are highly sociable, all of them are expected to accept the task. However, due to being very close to D_{max}, u_3 has a corresponding recruitment factor r_3 close to 0. Hence, the user is not contacted under DBRM. Instead, under SDRM, the sociability factor mitigates the bad score given by the distance, and u_3 is contacted for recruitment. As a result, the organizer sustains a cost equal to 3 and 2 units with SDRM and DBRM, respectively.

IV. Performance Evaluation

This section illustrates performance evaluation of the proposed user recruitment policy for data acquisition in mobile crowdsensing systems.

To evaluate and assess efficiency of the proposed recruitment policies, we have built a custom simulator where users move in a real city setting in the City of Luxembourg. It covers an area of 1.11 km^2 and is the home of many national and international institutional buildings. The information about the streets of the city is obtained from a crowdsourced application which provides free access to street-level maps[1] in form of a set of coordinates C containing <*latitude, longitude, altitude*>, see Fig. 3(a).

The participants move along the streets of the city and their original location is randomly assigned from the set of coordinates C. The number of participants ranges from 1 000 to 10 000, which corresponds to nearly one tenth of the population of Luxembourg (107 340 inhabitants as of late 2014). For simplicity, the start time of the walk is uniformly distributed between 8:00 AM and 1:30 PM. Each participant has only one mobile device and walks for a period of time that

[1]DigiPoint: http://www.zonums.com/gmaps/digipoint.php

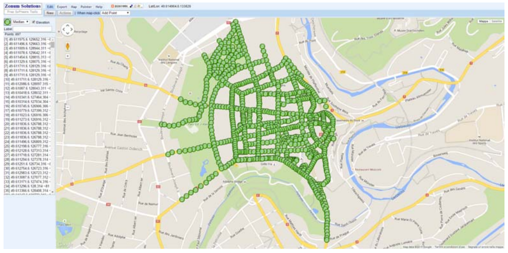
Table II
Simulation settings

Parameter	Value
Number of users	[1 000 - 10 000]
Overall evaluation period	8:00 AM - 2:00 PM
Time of travel per user	Uniformly distributed in $[10, 30]$ min
Average user velocity	Uniformly distributed in $[1, 1.5]$ m/s
Timeslot duration	1 minute
Task duration	$\{20, 25, 30, 35, 40, 45, 50\}$ timeslots
Number of tasks	25
D_{max}	30 m
Popularity factor p	$\{0.2, 0.4, 0.6\}$

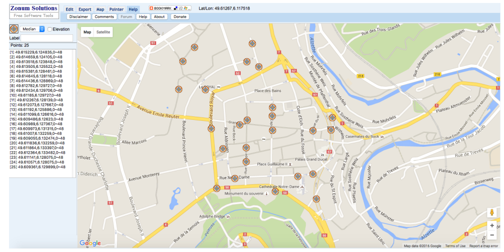
is uniformly distributed in $[10, 30]$ minutes with an average speed uniformly distributed in $[1, 1.5]$ m/s. The participants push data to the collector while walking. Once the period of walking ends, they stop moving and contributing. As a consequence, users can contribute for only a small portion of the day, which allows us to study the system performance under a relatively worst case scenario.

As an assumption, the maximum distance D_{max} within which users are considered eligible for selection is set to 30 meters. A set of 25 tasks is deployed in different locations of the city, see Fig. 3(b) for the details. Each task lasts 30 timeslots and each timeslot corresponds to 1 minute. For simplicity, in this first set of experiments the popularity factor of each location is fixed and set equal to 0.2. Table II lists the details on the simulation settings.

Having fixed the number of users during the evaluation period to 10 000, Fig. 4 shows the number of contacted and recruited users per task. The number of contacted users corresponds to the cost the system sustains for recruitment. The SDRM achieves a higher number of recruited users, but with a higher cost. In terms of number of recruited users, SDRM improves DBRM by a factor of two with an increase of the cost of around 35%. This is because users that are located at distant location are contacted if their sociability factor is high. Conversely, under the DBRM such users are never eligible for selection. Indeed, being far from the sensing task location, their recruitment factor is low. As a result, the number of effectively recruited users is low if compared with the number of users recruited in SDRM. Fig. 5 shows the average number of contacted and recruited users per task. SDRM outperforms DBRM under the current evaluation set-

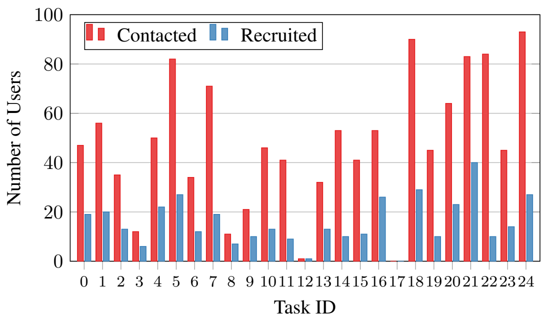


(a) Street-level information



(b) Location of sensing tasks

Figure 3. Map of Luxembourg



(a) SDRM

(b) DBRM

Figure 4. Cost and number of recruited users

Figure 5. Average number of users contacted and recruited per task

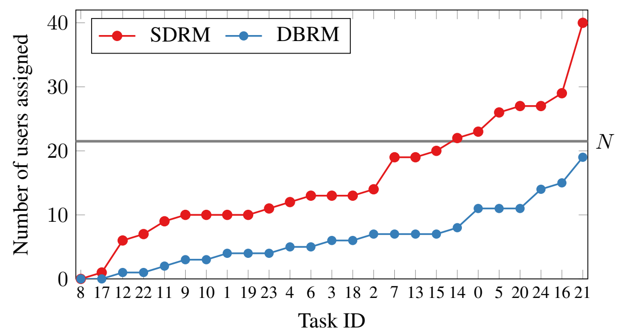


Figure 6. Number of assigned users per task

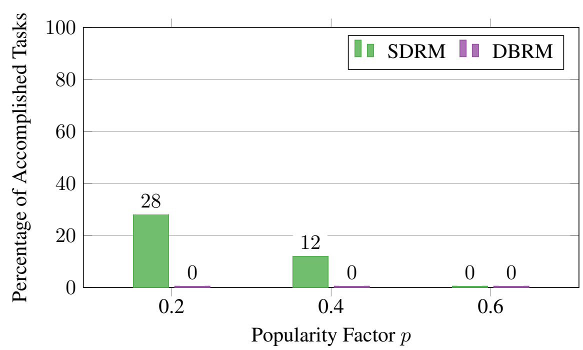


Figure 7. Accomplished tasks with increasing location popularity

ting. Indeed, the number of accomplished tasks is respectively 7 and 0 for the two modes.

To better understand the number of completed tasks under each mode, Fig. 6 details the number of unique users assigned to each task. The gray line plots N, the minimum number of users necessary to denote a task as accomplished. N is computed by (4) and is equal for all the tasks as the location popularity and the task duration have been fixed. Consequently, partial relaxation of any of the constraints on task completion would increase the number of accomplished tasks. As it is possible to see, SDRM accomplishes 7 tasks out of 25 and 3 more are close to completion. On the other hand, DBRM does not accomplish any task although one is close to completion. Only the campaign organizer can compare the tradeoff between cost increase and return, and pursue proper measures, e.g., to reduce the cost of user recruitment.

The previous experiments were conducted having fixed the location popularity of the tasks. Fig. 7 shows the number of accomplished tasks with increasing popularity factor in the system. For analysis, all the tasks are set with the same popularity factor p where $p \in \{0.2, 0.4, 0.6\}$. As expected, for low values of p, the SDRM always outperforms the DBRM, and the number of accomplished tasks decreases with the increase of p. Indeed, p is one of the parameters defining N, the minimum number of users necessary to denote a task as accomplished and the relation between p and N is proportional, see (4).

The following analysis aims to assess the impact of the total number of users in the system. For the experiment, the task duration is set to 40 timeslots and the popularity

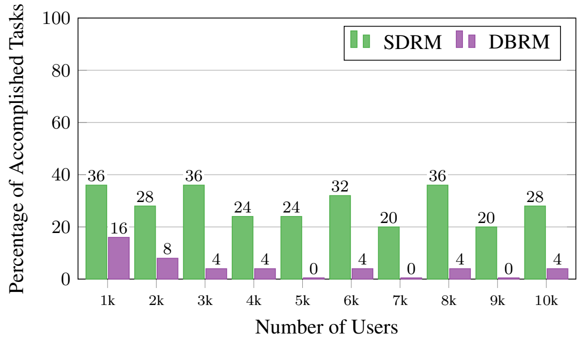


Figure 8. Accomplished tasks with increasing number of users in the system

factor is set to 0.2 for all the tasks. Fig. 8 shows that both modes are insensitive to the number of users. From a global perspective, indeed, high system performance is guaranteed if a high number of users find themselves close to the location of the sensing tasks when they are deployed. The sole exception is the DBRM, as when the number of users is medium-low, the number of accomplished tasks decreases with the increase of the population. A low total number of users in the system reduces N, which is the threshold defining tasks as accomplished, see (4).

V. Conclusion

Recruitment policies define the criteria for user eligibility to contribute data to mobile crowdsensing systems. Proper recruitment is important as it allows to minimize the cost sustained by the system and maximizes the return, such as the number and the accuracy of accomplished tasks.

In this paper we have proposed a novel user recruitment policy for data acquisition in mobile crowdsensing systems. The policy can be employed in two modes. The distance-based recruitment mode (DBRM) recruits users on the sole basis of their distance with the sensing target. The sociability-driven recruitment mode (SDRM) employs both user distance and sociability as selection criteria. We investigated the performance of the two modes in a real urban scenario with a large-scale number of users. The results showed the effectiveness of including sociability to determine user eligibility. SDRM improves DBRM by a factor of two in terms of the average number of recruited users. Furthermore SDRM always outperforms DBRM in terms of number of accomplished tasks. Even under an extreme case where DBRM fails to complete any task, SDRM can still accomplish 10% of the tasks.

We are currently extending the proposed policy through finer modeling of sociability and including energy spent for contribution as additional criterion.

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