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A stability-based group recruitment system for continuous mobile crowd sensing

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ABSTRACT

With the proliferation of Mobile Crowd Sensing (MCS), many domain applications that answer different sensing requests, have been benefiting from the availability of participants in areas of interest (AoI). These requests have been commonly classified as one time sensing or continuous sensing requests. In the former, one-time reading from the devices of the recruited participants is needed to answer the request, while in the latter, readings are needed over a given time interval, making recruitment challenging, particularly when considering participants' mobility. Ideally, the process of recruiting participants for a given continuous sensing task should determine the best set of participants to answer the sensing requests, while satisfying two important constraints including (1) a given level of quality of information (QoI) and 2) within a given budget. This selection is also sensitive to parameters such as requirements of the sensing task with regards to the AoI coverage, and participants' mobility and distribution. To address this challenge, we propose a novel, stability-based group recruitment system for continuous sensing (Stable-GRS) that employs a genetic algorithm to select groups of participants considering their mobility patterns. The proposed system selects the most stable group of participants in the AoI that can achieve a certain level of QoI, where stability reflects the group's temporal and spatial availability. The process of recruitment is dynamic; it involves adding and removing participants throughout the sensing period to preserve the QoI requirement. Cooperative game theory, specifically the Shapley value, is used to reward selected workers based on their respective contribution. Simulations are conducted using real-life datasets and the results establish that our approach outperforms an individual-based recruitment system (IRS), which employs greedy algorithms to recruit participants for all key performance metrics, such as the QoI and costs.

1. Introduction

Mobile Crowd Sensing (MCS) [1] is a people-centric sensing paradigm that allows obtaining knowledge about a wide range of dynamics using powerful mobile devices [2]. In an effort to obtain more flexibility with less cost, MCS systems were developed to cope with the weaknesses of the existing sensing networks that are known for their inflexibility and high deployment costs [1]. Nowadays, there is a wide range of applications in which MCS plays a pivotal role [3] such as traffic monitoring [4], urban sensing [5], observation of environmental conditions [6], noise maps generation [7] and environment pollution assessment [8].

With the emergence of MCS systems come various new challenges. These challenges may concern task publishers, participants, and/or the management platform. They may also be related to the infrastructure used. Sensing tasks may come in different forms with various sets of requirements and constraints. These sensing tasks are classified as one-time sensing requests or continuous sensing requests that span over a period of time. In the former case, participants locations at a particular time is needed for the management platform to select suitable participants for task completion. However, in the latter case, participants need to stay connected to the management platform, through the available communication links, in order to submit the required sensing reports even while changing locations. As opposed to one-time sensing, in continuous sensing many parameters may change abruptly during the course of the sensing period. As an example, a participant selected at the beginning of the sensing period may leave the AoI during the same period. In this case, the management platform needs to be adaptive and should have a mechanism to replace this participant or have a process in place to avoid degradation of the quality of the sensed data. The dynamic nature of continuous sensing, as opposed to one time sensing, causes the quality of submitted reports to fluctuate, and in some cases

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to drop below the desired level throughout the sensing period. Hence, it presents a whole new paradigm in MCS.

1.1. Problem statement and motivational scenario

In MCS systems, the quality of the reports submitted by the participants typically depends on parameters that can be classified into three main categories: AoI-, device-, and participant-related parameters, as explained in [9]. In continuous sensing, some parameters need to be given special consideration, such as the mobility of a participant and the duration of her/his connectivity to the management platform. For example, monitoring how the weather changes over an entire day is an application that requires continuous sensing, which implies collecting readings from participants' devices many times over the sensing period. Since the recruited participants may be mobile, it is necessary to consider their mobility in the selection process to guarantee AoI coverage and meeting the publisher's expected level of quality, in return for the provided budget.

Typically, in current MCS systems, QoI is evaluated for each participant [10–15] and those who provide acceptable QoI are recruited. Adopting an individual-based recruitment system has some inherent weaknesses. To overcome such weaknesses, a novel group-based recruitment system was proposed in [9]. For a one-time sensing task, the group-based recruitment system selects the most appropriate group of participants within a given budget, for a maximum QoI. Since the group of participants is selected only once in this system, it is not directly applicable to continuous sensing tasks. Indeed, the group, the group dynamics, or the QoI itself may change during the sensing task.

To illustrate this fact and to study the mobility impact on the QoI of group-based recruitment for a continuous sensing task, simulations were conducted using the vehicular mobility traces of the city of Cologne, Germany [16,17]. The simulation parameters are as follows:

- AoI: $(5000\,m) \times (5000\,m)$
- AoI is divided into 25 identical sub-regions
- Sensing period: the experiments lasts for 250 s
- Required data: traffic condition

The one time sensing GRS recruits the group that is expected to provide the best QoI at the beginning of the sensing period i.e. at $t = 21600\,s$. The group remains unchanged throughout the sensing period, and hence, ignoring any potential change in QoI over time. To show that mobility has a profound effect on QoI, an experiment was conducted, where the QoI was reevaluated every 60 s for the same group, as shown in Table 1. As can be seen from the table, a 28% drop in QoI is observed at the end of the sensing period. This is primarily due to reasons such as - participants leaving the AoI before the sensing period is over, participants losing connection with the management platform, or movement of the participants causing uneven distribution in the given AoI (as shown in Fig. 1). Hence, the spatio-temporal availability of participants for continuous sensing is highly affected by the mobility of participants. This necessitates the need for reselection of the group periodically to assure that a certain level of QoI, as set by the task publisher, is maintained throughout the sensing period.

In this example, one-time sensing GRS was run every 60 s to reselect the group to achieve the maximum possible QoI. In addition, the QoI was monitored to see the impact of mobility on the sensing outcome. Two facts were noticed: first, by decreasing the duration between two re-selections, the time that the system spends to complete the recruitment process increases accordingly. Second, as shown in Fig. 2, during the 60 s between every two re-selections, QoI drops below its initial value due to the mobility of the participants and the changes in their respective characteristics. For instance, the group selected in the interval starting at 21600s provided a QoI that answers the task requirements. At the end of this interval, the QoI provided by the selected group dropped to a level that is 20% less than the required QoI. This fact confirms the need for a dynamic approach that deals with the variations in QoI in a timely manner.

Table 1
Using one-time sensing GRS for continuous-sensing tasks.

Time(s)	Participants in AoI	Coverage	Distribution	QoI
21,600	Fig. 1a	0.56	0.69790	2.905164
21,660	Fig. 1b	0.36	0.4500	2.457237
21,720	Fig. 1c	0.28	0.3615	2.288737
21,780	Fig. 1d	0.2	0.2494	2.096637
21,840	Fig. 1e	0.08	0.3684	2.095637

This experiment shows that a recruitment system for continuous sensing tasks should not only satisfy the requirement of the sensing requests at the beginning of the specified sensing period, but should dynamically add or remove participants based on the QoI, avoiding participant re-selection whenever possible. The system should also pay participants based on their real contribution to QoI, as this may differ from one participant to another and from one instant to another during the sensing period. Hence, this paper proposes a recruitment system, referred to as the Stability-based GRS, designed for continuous sensing. This system provides a novel solution for the aforementioned challenges.

1.2. Contribution

To answer the challenges of participants' recruitment in continuous sensing, we propose a novel recruitment system based on stability, the spatio-temporal availability of participants in the AoI over the specified time period, and the impact of participants' mobility on the QoI parameters. As participants' contribution is not equal, a mechanism for rewarding participants is proposed to fairly pay them based on the marginal benefit of their reports to the sensing outcome/quality. The contribution of this paper is summarized as follows:

1. The design and development of a recruitment system for *continuous-sensing* tasks in MCS systems, Stability-based GRS.
2. The development of a new method to recruit groups of participants based on their stability in the AoI, over the sensing period, to answer continuous sensing tasks using a genetic algorithm by taking participants' mobility into consideration.
3. The use of cooperative game theory, represented by Shapley value [18], to reward fairly the selected workers based on their contributions to the overall QoI during the sensing period. Shapley value states that rewards are distributed among a number of participants in the order of the importance of their contributions in the cooperative activity. In other terms, the more a participant contributes to the group's outcome, the more they are paid back.

Testing and evaluation of the proposed Stability-based GRS for continuous sensing tasks was done using the vehicular mobility trace of the city of Cologne, Germany [16,17]. Applicability of the proposed system is compared to one-time sensing GRS [9], when used for continuous sensing tasks, to evaluate the practicality of the proposed approach. It is also compared to the individual-based recruitment approach. The results show that the Stability-based GRS outperforms the benchmark in terms of the achieved QoI, group size, and the consumed budget.

1.3. Paper outline

The rest of this paper is organized as follows: Section 2 summarizes the various recruitment frameworks proposed in the literature, Section 3 thoroughly explains the suggested model followed by the proposed approach in Section 4. Simulations of the proposed solution