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A Survey on Participant Recruitment in Crowdsensing Systems

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***Abstract*—Advances in the sensing capabilities of smartphones have resulted in the emergence of crowdsensing. In a crowdsensing campaign, ordinary citizens are recruited to collect sensor data from nearby environments which are then analysed to provide useful information. In order for a crowdsensing application to be a success, sufficient number of well-suited participants should be recruited to contribute. In this paper, we make a review on the works presented to address the challenge of participant recruitment in crowdsensing systems. We first have a short review on the related works in the area of online communities and crowdsourcing systems. Then, we present a review of the works specifically related to crowdsensing systems.**

I. Introduction

The widespread presence of mobile computing devices such as sensor-equipped smartphones has led to the emergence of a novel sensing paradigm, known as *participatory sensing* [1] or *Crowdsensing*. In crowdsensing, ordinary people use their mobile phones voluntarily to gather sensor data from their nearby environment. Such sensor data gathering is aimed at computing the aggregate statistics about a phenomenon and hence, increasing the global awareness of issues of interest [9]. A great number of applications have been recently proposed based on this emerging paradigm. In PetrolWatch [2], a mobile phone is mounted on the dashboard and automatically captures photos from roadside fuel price boards when the car approaches a fuel station. The photos are then uploaded to a server which is responsible for extracting the fuel price via image processing techniques. Individuals query the server to obtain the cheapest fuel price in their vicinity. In LiveCompare [3], participants are recruited to take photos of price tag and the barcode of products. The barcode is decoded into a textual representation on the mobile phone, and submitted to the server along with the picture displaying the current price. Other information such as the location/time of capture are also stored in the server. Users are then able to search for products in the application in order to compare prices. The server retrieves reports about the corresponding price, selects the stores which are near to the user's current location and shows the pictures of the related price tags. In a series of other applications such as NoiseTube [4], Ear-Phone [5] and NoiseMap [6] mobile phone microphones are used to measure the surrounding noise level. The sound samples are used to build typical noise pollution maps of urban spaces to enable specialists to understand the relationships between noise levels and behavioural problems.

The inclusion of people in the process of sensor data collection, however, leads to new challenges [51]. Contributing to a sensing campaign will inherently needs that the participant devotes some time and effort to accomplish it. Moreover, collecting and uploading the sensor data consumes the communication bandwidth and mobile phone battery. Most importantly, engaging in such crowdsourcing activities may result in potential privacy threat such as the disclosure of home/work address or private conversations [7], [8], [9]. Further, participatory sensing systems are based on voluntary participation and typically there is little incentive for contributors. Considering all these challenges, a participant may be hesitant to participate in a sensing task. This may result in a lack of sufficient participation, which in turn may compromise the fidelity of the obtained information and ultimately render the application to be not very useful.

Besides, some tasks may require that the participants have specific knowledge or expertise related to the task at hand [10]. For example, consider an application that is aimed at collecting the photos of rare plant species. In order to obtain high fidelity pictures, the requester may wish to recruit participants who have some knowledge of botany. In general, it is desirable to recruit suitable participants (who are those who can fulfil the requirements of the task at an acceptable level). To sum up, an important challenge in obtaining trustable results is the recruitment of participants who are (i) sufficient in number and (ii) well-suited to contribute to the task.

This survey aims to present a review on works addressing the participant recruitment issue in participatory sensing. In order to have a better understanding on the related works in a broader view, we first have a short review on the related articles in the domain of online communities and crowdsourcing systems. We then focus on works specifically addressing the recruitment challenge in crowdsensing systems.

The remainder of the paper is as follows. Section II reviews the works concentrating on worker recruitment issues in online communities. Section III presents the articles aiming at addressing the participant selection challenge in participatory sensing. Finally, Section IV concludes the paper.

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II. Participant Selection in Online Communities

Crowdsourcing systems enlist a multitude of humans to help solve a wide range of tasks defined by the system owners [34]. The requester defines the task and submits it via a crowdsourcing platform (e.g. Amazon Mechanical Turk). Workers then choose to contribute and submit their contributions.

Crowdsourcing systems commonly use one of three worker selection approaches: Open-call, qualification-based, and publish-subscribe [21], [22], [25], [26]. In the following, we discuss these approaches in detail.

A. Open-Call

In this approach, there is no participant selection and each worker is able to contribute to the task. Wikipedia, Threadless, [1] and the ESP game [27] use this approach, which is simple to implement and easy to use. For example, in Wikipedia, anyone can edit almost every page. In Threadless which is an online community of artists, designers submit their work online. These works are put to a public vote and each member is able to vote for his favourite design. Also in the ESP game, each user can take part in the image labelling game and receive incentives. While this openness, which can result in and gather members with different knowledge, expertise and interests, is an advantage of crowdsourcing, it may lead to selecting low quality workers and make quality assurance particularly challenging.

B. Qualification-Based

This approach uses qualifications to select workers. The worker's qualification is affected by a series of parameters such as the quality of his previous work, number of his approved works, his skills, reputation [24], etc. Thus, smaller bespoke crowds can be assembled out of the workforce to contribute to highly specialized tasks [26]. Amazon Mechanical Turk is an example of the systems that utilise this approach [23], [28]. The requester can use qualifications to control which workers can perform his HITs (Human Intelligence Tasks). A HIT can have requirements related to the qualification of the worker which have to be fulfilled before the worker is allowed to accept the HIT.

Among the set of qualifications, reputation is probably the most important parameter. Reputation is in fact an overall estimation of a worker's quality and trustworthiness. Although reputation-based approaches have well-engineered foundations, they are prone to various types of attacks [22], [29]. The attacker may aim to raise or downgrade reputation scores of specific entities. These entities may either benefit from or lose advantage as a result of reputation score manipulations when competing with similar entities for users' preference. In traitor attacks, the worker achieves reputation by showing good performance until the reputation score is recovered and then returns to bad behaviour again. In other words, he performs well and badly alternatively, with the aim of keeping the reputation score greater than a certain threshold.

[1] http://www.threadless.com

Expertise is another important parameter in the qualification of participant. Expertise-based participant selection consists of identifying users with relevant expertise or experience for a given topic [51]. Expert finding has been extensively investigated in social networking [30], [31], [32], [33]. Authors in [32] developed a Bayesian hierarchical model for expert finding that considers social relationships as well as content. The model assumes that expertise similarity between candidates defines social links between them. Authors in [33] propose a two-step propagation based approach to find an expert in a social network. In the first step, an initial expert score for each person is estimated based on his local information, and then, the top scored persons are selected as candidates who are used to establish a sub-graph. In the second step, expert score propagation is performed from one person to the others with whom he/she has relationships.

C. Publish-Subscribe

In this approach, tasks are assigned based on a publish/subscribe service. In particular, by subscribing to the serve, the participant (subscriber) shares his interests and preferences about a topic, and messages are forwarded only to the interested participants by the requester (publisher) [21], [25]. The main challenge in this approach is the lack of sufficiently qualified participants to contribute to tasks that need specific knowledge or expertise [26], [34].

In addition to the shortcomings mentioned above, the main challenge in the above mentioned participant selection methods is their vulnerability to the colluding attacks. A group of malicious workers might form a colluding group with the aim of attacking the task, so that they are recruited as honest workers. The colluding group would then contribute polluted data with the aim of swaying the result of the task in accordance with their agenda.

III. Participant Selection in Crowdsensing

In participatory sensing applications where participants are typically recruited to contribute to the tasks with defined spatiotemporal specifications, new selection criteria are brought up in addition to the general parameters. In the following, we discuss the related works in the area of participatory sensing in detail.

A. Coverage-based Recruitment

The tempo-spatial coverage is the first matter for most of the participatory sensing campaigns to consider. In [35], [10], [36], campaign-specific metrics have been proposed for the identification of well-suited participants. These metrics include a set of parameters. The first parameter is called coverage, which represents the availability of the participant in terms of space and time. In order to extract the geographical and temporal availability, location traces in the form of latitude, longitude and time points are collected and analysed for a period of time. The second parameter is called timeliness, which represents the delay between the event happening and the time when the sample is available to be precessed. The third parameter is called capture, which is related to the quality of a sensing sample determining the capability of pointing out a particular feature in it. The fourth parameter is called relevancy, which specifies how much the sensor reading is successful in describing the event intended to capture. The last parameter is called responsiveness which specifies the probability of responding to a directed sensing request.

Authors in [42] proposed participatory texture documentation (PTD) implementation in two steps. The first one is viewpoint selection which selects minimum number of points in target area from which, it is possible to extract the texture of the entire environment with a desirable quality. At the second step (i.e., viewpoint assignment), the participants are assigned the previously-selected viewpoints in a way that given a limited number of participants with different constraints such as time, they can collectively gather the maximum amount of texture information considering the time limit.

Also in [37], authors propose a distributed recruitment framework for participatory sensing. In their proposed framework, the suitability of a participant behaviour is defined by considering the history information of his mobility, and only those who are likely to be in the sensing area when the sensing activity is occurring are going to be recruited. Before the start of the sensing campaign, a group of recruiting nodes visit the target sensing area and then, disseminate recruitment messages. A set of nodes called data sinks are also used that are responsible for transferring collected sensor data to the requester. Ad hoc encounters are then exploited by participating nodes opportunistically to adhere to these data sinks temporarily deployed in the sensing area.

In [41], authors proposed a recruitment method for real time (dynamic) and heterogeneous tasks with the aim of minimizing sensing cost as well as maximizing level of probabilistic coverage. In order to minimize the cost, they aim at employing the least number of participants. Moreover, to estimate the call probability of users in a specific location, they consider historical call and location traces. Their proposed method has been setup in two offline and online modes. In the offline mode, the participant with the largest coverage ratio is selected at each round and the recruitment process will finish when all the interested area is covered before the deadline. Offline algorithm is based on historical call data from participants and its prediction cannot be accurate and trustable, thus the actual coverage ratio could be much less than the estimation. Online algorithm checks whether current participants fulfill the task and if not, it greedily selects the new participant to maximize the level of coverage.

Authors in [44] focus on task assignment problem in mobile crowdsensing systems, considering the mobility model of participants in mobile social networks (MSN). They first assume that task assignment can be done only when the requester meets other participants with some probabilities. To solve the problem, they propose two offline and online task assignment methods. In the offline case, the requester always assigns the tasks to the earliest idle participant, that is, the participant who has the minimum expected time to complete the assigned tasks. Moreover, in the offline mode, participants are assigned tasks based on the ascending order of tasks' workloads. In this way, the requester is able to obtain the optimal outcome. In the proposed online assignment approach, when the requester encounters each mobile user, he repeatedly performs the previously-mentioned offline greedy task assignment until all tasks are assigned. More specifically, when the requester meets a participant, he first computes the Instant Processing Time (IPT) of the user and Expected Processing Time (EPT) of other participants who have not been encountered yet. He, then, assigns the minimum workload task to the participant who has the least amount of IPT until all tasks are assigned.

In [46], authors explore the task allocation problem by considering the mobility paths of mobile users, specifically, the geographical specifications and characteristics of sensing tasks as well as the spatial movement limitations of mobile users. Moreover, they assume that in order to provide the required quality of sensing, the same sensing task may be required to be performed by multiple mobile users. Authors then propose an approximation algorithm to solve the allocation problem. They also design a pricing mechanism for reaching agreement between mobile users and the platform on the prices of sensing tasks.

[47] proposes a recruitment framework for spatial crowdsourcing in which, only those workers who are already within the spatiotemporal vicinity of a task are eligible candidates to contribute. Then, a subset of candidate participants whose size is constrained by a predefined budget, are selected to perform tasks. The challenge is to maximize task coverage under budget constraint, despite the dynamic arrivals of participants and tasks. Two problem variants have been studied, one with a given budget at each time period and the other with a given budget for the entire task period. To solve these variants, three different heuristics have been proposed, utilizing the spatial and temporal properties of tasks.

Authors in [38] consider the tempo-spatial behaviors of participants as a selection criterion. To assess the participant's tempo-spatial behavior, they utilize an association matrix in which, rows are location grids which constitute the intended task locations and columns represent time periods along a day. Each matrix element shows the percentage of elapsed time for a specific participant.

B. Reputation-based Recruitment

The 'reputation' of a participant is the overall quality or character as seen or judged by people in general. In other words, reputation is a community-wide opinion generally held about someone [20].

Multiple works have considered reputation as a prominent parameter in participant recruitment. In [35], cross-campaign metrics are presented that provide a granular view of a participant's past performance during many tasking campaigns. They include number of: previous campaigns volunteered, participated in, and left. These parameters are then combined to determine the overall reputation for the participant on a per task basis. However, in [10], the term reputation is limited to taking into account the participants' willingness (given the opportunity, is data collected) and diligence in collecting sensor readings (timeliness, relevance and quality of data).

Authors in [16] propose a reputation-based framework which calculates and assigns a reputation score to each sensor node by utilising a Beta reputation function. The advantage of Beta reputation is its simple updating rules as well as easy integration of ageing. However, it is does not punish users with poor quality contributions aggressively. In [15], a reputation framework for participatory sensing was proposed. Based on the short-term behaviour of each device, a cooperative rating is computed for it by the watchdog module. This rating then acts as input to the reputation module which is responsible for building a long-term reputation score by utilizing Gompertz function.

In [38], authors represented a Selfadaptive Behavior-Aware Recruitment scheme (SBR) for participatory sensing which selects high quality participants by considering their tempo-spatial behaviors and quality rating of the provided data considering budget limitations. In order to assess the reputation of the participants, five parameters are being considered, mainly, accuracy, timeliness, completeness, relevance and redundancy which are combined to form a reputation score. This score will be further used to calculate the quality of participant's provided data. The proposed method is self-adaptive in a way that it dynamically observers the quality of the provided data for each participant and removes incapable participants if they provide low-quality data for a specific task duration.

Authors in [17], [18] proposed a trust-based recruitment framework for social participatory sensing. In their proposed method, to identify and select suitable and trustworthy participants, multi-hop friendship relations between friends or friends of friends in a social network are utilised, and the most trustable paths to them are also identified. In order to assign a trust score to the participant, a set of personal parameters such as participant locality score to different geographical areas, his expertise and his timeliness in reacting to sensing tasks are considered. Moreover, social parameters such as friendship duration between participant and each of his friends, and the timegap between their successive interactions are also considered. Authors then extended their work in [20] and for each participant, a reputation score is calculated by utilising the PageRank algorithm, which is then used as a prominent factor in selecting the suitable participants.

Authors in [40] proposed a reputation calculation and update method. The aim is to define a reputation score for each participants as a criterion in selecting the most appropriate participants. They also considered budget limitation and helping participants to choose the proper task for maximizing their rewards. They introduced two metrics : DOT and QOI satisfaction. DOT (Difficulty of Task) metric for specific task is calculated by the participants which shows the task degree of difficulty. Based on it, the participant decides whether or not to contribute. DOT is calculated based on a set of factors such as the sensor types needed for each task, sensing time slot and the remaining energy of the device. QOI (Quality of Information) measures satisfaction ratio of collected data compared with task requirement based on data quality, granularity and quantity.

C. Expertise-based Recruitment

Expertise is another important parameter in the qualification of participant. Expertise-based participant selection consists of identifying users with relevant expertise or experience for a given topic.

Authors in [39] investigate the problem of task assignment for heterogeneous classification tasks in which, workers provide labels for instances. In their proposed solution, they aim at having an estimation of the worker's skill levels and the quality of their provided labels. They then used a near optimal adaptive assignment algorithm that adaptively assigns tasks to the workers based on these parameters. Authors also considered an offline settings in which the worker's skills and capacity (max number of tasks intended to complete) are known in advance. Their results show that adaptively assigning workers to task will lead to more accurate predictions at a lower cost.

In [45], an online task assignment algorithm is proposed in which, the task owner has a fixed set of task and wishes to assign them to a set of workers with unknown, heterogeneous skills, and a budget for each task that specifies the maximum number of times he would like the task to be performed. Skill levels are unknown at first, but can be learned through observations as workers complete tasks. This leads to a natural trade-off in which, the requester must observe the performance of each new worker on different tasks to estimate her skills, but would prefer to assign a worker to the tasks at which she performs well. Results show that their proposed method is competitive with respect to the offline optimal when the number of worker arrivals is large.

D. Budget-based Recruitment

In typical participatory sensing applications, volunteer participation is the basis of the work and normally no explicit incentives is given to participants in return for their contributions. During the contribution to a task, the participant's private resource such as battery and computation power of his device will be consumed. Moreover, potential location privacy threats may be exposed to the participant. Taking these issues in consideration, the participant may be hesitant to contribute to the sensing campaign without obtaining explicit benefits. To address this issue, a series of related works propose different incentive mechanisms as a driving force for user participation. In such works, the requester assigns to each task a specific budget at the time of task creation and this budget is dynamically allocated to task contributors. The aim is then recruiting more suitable participants under budget constraints.

A comprehensive series of works such as [48], [49], [50], [51], [43] have been proposed to recruit participants considering the allocated budget.

Authors in [48] conducted an study to investigate the effect of micropayments as an incentive mechanism. They defined micropayments as transactions in which small tasks are matched with small payments. In this study, 5 different micro-payments, i.e., a lump sum payment (MACRO), medium micro-payment (MEDIUM), high micro-payment (HIGH), low (LOW), and competition-based (COMPETE) are used. The obtained outcomes show that that, if mixed with altruism and competitiveness, monetary incentive will be beneficial. In particular, they found that HIGH and MEDIUM were the most successful methods, MACRO and LOW resulted in poor outcome in terms of the number of submitted data. Moreover, for short bursty data collections, dynamic incentivising methods such as competition could be more appropriate.

In [43] authors proposed data quality oriented heterogeneous participant recruitment strategy for vehicular participatory sensing. They aimed at selecting a set of well-suited participants who can collect high quality tempo-spatial data with a limited budget. The proposed strategy aims at modelling the optimal participant recruitment problem that assesses participant's performance by considering the differences between the requirements of sensing data and the sensing data collected. Moreover, based on the utility of vehicles, a greedy algorithm is designed with the aim of recruiting the most efficient vehicles with a limited total incentive budget.

The work in [49], [50] proposes a dynamic pricing method which enables participants to sell their data by attending in a dynamic price reverse auction system. More specifically, in the proposed Reverse Auction-based Dynamic Pricing (RADP) incentive mechanism, a predefined number of lower bid-price participants are chosen by the service provider, and the selected users are given their bid prices as a reward. Thus, the selling price changes dynamically according to the users' bid prices.

The proposed scheme in [51] first utilises a series of certain suitability parameters such as expertise, reputation, etc. to identify a set of candidates as potential participants. the most suitable participants are then chosen by considering their desired bids and the budget specified by the requester. Once the sensor data is collected, the reward is allocated to participants based on the contribution quality as well as the quality of contributions made by their social friends (who are motivated to participate by them). Results of their simulation showed that their proposed method is effective in recruiting a greater number of participants since it encourages and motivates participants to invite their friends in order to achieve more reward.

IV. Conclusion

Recruiting sufficient number of well-suited participants has been a major challenge in the success of crowdsensing systems. Privacy challenges and battery and bandwidth usage are some of the main consequences of task contribution, which may lead to the less willingness of users to participate. In this paper, we present a short review on the works aiming at addressing the participant recruitment in crowdsensing systems. Specifically, we categorise the state-of-the-art based on a set of participant selection criteria such as coverage, reputation, expertise and budget constraint. In future, we will extend the work to cover more recent and subtle works with excessive descriptions.

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