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EFFICIENT APPROACH OF CHANNEL STATE INFORMATION PREDICTION FOR 5G NETWORKS USING CROWD SENSING OPTIMIZATION ALGORITHM

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Abstract-In mobile crowdsensing (MCS), among the participants' main concerns is the cost for 5G data usage, which influences their willingness to take part in a Crowdsensing task. In this paper, present the look and implementation of an MCS info uploading mechanism CSI prediction in reducing additional 5G data cost incurred by the complete crowd of sensing participants. By taking into consideration the two most common real-life 5G price plans-unlimited data plan (Unlimited) and pay as you go (Payout PER), CSI prediction partitions all of the users into two teams corresponding to these two price plans at the beginning of each month, with the aim of minimizing the total refunding budget for all individuals. The partitioning is founded on predicting users' mobility patterns and sensed info size. The CSI prediction mechanism was created influenced by the observation that during the data uploading cycles, Unlimited users could opportunistically relay Shell out PER users' info to the crowdsensing server without extra 5G price, pro- vided both types of users will be able to "meet" on a common native cost-no cost network (e.g., Bluetooth or WiFi direct). To carry out the experiments using both Massachusetts Institute of Technology fact mining and the tiny World In Action (SWIM) simulation data sets. Analysis results exhibit that CSI prediction could lessen total 5G data expense by up to ~50%, in comparison with the direct-assignment approach that assigns each participant to Unlimited or PAY PER directly according to the size of her sensed information.

Keywords : 5G data cost, data relay, delay-tolerant data uploading, incentive, mobile Crowdsensing (MCS).

I. INTRODUCTION

Mobile crowdsensing (MCS) [1], [2] is becoming an effective and practical way to carry out various sensing tasks, as rich-sensor equipped smartphones are getting more and more popular. However, some obstacles severely stop users from participating in MCS tasks. For example, participating in MCS tasks will incur additional 5G data usage for a user, which might lead to more fees paid to the telecom operators. This issue, which will refer to as 5G data cost, is one of the major concerns for MCS participants [3], [4].

To deal with this issue, some existing MCS projects ask users to delay uploading sensed data until they have a WiFi connection; apparently this method might lead to long uncontrollable delay between data sensing and uploading. Such a long uncontrollable delay might harm many MCS tasks. On one hand, uncontrollable delay might not be tolerable for most real-time monitoring applications, as the delayed sensed data becomes valueless; even if an MCS task allows some delay, uncontrollable delay may still exceed the maximum tolerable delay. On the other hand, long uncontrollable delay increases the probability of sensed data loss due to abnormal events on participants' mobile phones (e.g., running out of storage space).

Another effective way to mitigate participants' 5G data cost concern is providing participants with incentives to cover any additional 5G data cost arising from participation in the MCS task. Compared to WiFi-only uploading, refunding 5G data cost encourages participants to willingly upload data at any specific time via 5G, which can reduce and control the delay between data sensing and uploading. However, 5G data refund increases an organizer's total MCS task budget. For MCS tasks which need a big number of participants, in particular, this 5G data refund budget can be significant. Thus, "how to reduce the 5G data refund budget" becomes a critical problem for MCS organizers.

In this paper, we try to address the above problem. First, we study the common price plans of 5G data cost. Currently,

sensed data size in a month can usually be estimated within reasonable error bounds (i.e., $d \approx d'$), which makes direct- assignment applicable.

Although direct-assignment can support real-time data uploading reasonably well, for many MCS tasks which do not require real-time uploading (i.e., allowing a max tolerable delay between sensing and uploading), the refund budget of direct-assignment may be very high. The following events can be leveraged to reduce participants' 5G data cost during the delay period, so that the organizer's refund budget can be reduced.

1) A PAY PER participant can use a cost-free network, such as Bluetooth or WiFi (e.g., at home or in the office), to upload sensed data to the server within the delay period, which reduces her 5G data cost.

2) Unlimited participants can help relay PAY PER participants' sensed data to the server. This kind of relay reduces 5G data cost for PAY PER participants, without increasing 5G data cost for Unlimited participants, thus decreasing the organizer's refund budget.

Based on these events, in this paper, we design a novel data uploading framework for MCS, called CSI prediction, whose goal is to optimally partition the participants into Unlimited or PAY PER subgroups, in order to minimize the organizer's 5G data refund budget, via maximum taking advantage of cost-free networks and mobile participants as data relays.

Two important issues are involved in designing CSI prediction.

A. How to Transfer Data When Two PAY PER Participants Meet. Unlike the clear relay strategy between a PAY PER participant Data and an Unlimited participant (i.e., PAY PER $\longrightarrow$ Unlimited), relay strategy between two PAY PER participants is more complicated and will affect the organizer's refund budget. Among all the possible strategies, flooding (i.e., always exchanging data between two PAY PER participants) is expected to produce the smallest refund budget. Because after flooding, if any one of two PAY PER participants could meet an Unlimited participant or a cost- free network, both of their data could be uploaded without 5G cost. However, flooding might incur too many redundant relays that rapidly drain the batteries of participants' mobile phones. Though this paper focuses on minimizing the organizer's 5G data refund budget, the participants' energy concerns should also be taken into account to some extent. Otherwise, even if CSI prediction "successfully" minimizes the refund budget, participant phones' energy consumption might be too high, making CSI prediction impractical. Thus, to study the tradeoff between the organizer's 5G data refund budget and participant phones' energy consumption, we try different data uploading/relay strategies following the state-of-the-art from our previous work [5], [6].

II. RELATED WORK

Recent years have witnessed an increasing interest in MCS research [1], [2], leading to many applications, such as urban noise monitoring [9], everyday point-of-interest tracking [10], and social interaction sensing [11]. Generic MCS platforms, such as Participant [12], have also been proposed to support various crowdsensing campaigns. As successful MCS tasks usually require a large number of participants, the question of how to incentivize users to participate is a key issue for MCS organizers. Potential participants need to have their concerns addressed, and current participants must not be discouraged by any inconvenience arising from the sensing process.

Previous research work about MCS incentives has leveraged game theory and auction mechanisms to analyze the optimal payment to be offered by the MCS organizer to participants and to find the best compromise between participants' and organizer's profit (i.e., the utility function in game theory) [13]. Some other work attempts to reduce the incentives by minimizing the number of recruited participants [14], [15] or amount of collected data [16]–[18], while ensuring a certain level of the task quality. As an alternative to monetary reward, some approaches offer other incentives such as service time [3] and coupons [19]. In general, these approaches assume the users' cost to finish a task to be known in advance, and this cost fol- lows some specific probability distribution in their simulation experiments. In contrast, our approach analyzes users' cost from a more pragmatic viewpoint—we focus on the 5G data cost, which has previously been shown to be a main concern for a majority of users [3], [4].

With respect to the objective of reducing 5G data cost, previous research work proposes to reduce the sensed data size based on mechanisms such as: 1) compression/aggregation of data on the phone [11], [20] and 2) uploading only a subset of the data while deducing the rest [21]. As CSI prediction is a data uploading framework, all the aforementioned mechanisms, which can reduce sensed data size before uploading, could be incorporated into CSI prediction to reduce users' 5G data cost further. Cost-free data uploading methods for MCS applications, such as user node relays [22] and delayed WiFi/Bluetooth transfers [5], [6], [23], have already been proposed in existing research work; CSI prediction uses similar mechanisms. However, by considering two common 5G data price plans—Unlimited and PAY PER—we identify a novel problem to minimize the MCS organizer's 5G data refund budget, through optimally partitioning the users to PAY PER/Unlimited groups and designing uploading strategies for users, so that Unlimited users can help relay PAY PER users' data efficiently.

Existing work concerning human mobility pattern prediction is also relevant, since CSI prediction predicts users' mobility patterns in order to determine the participant partition. Human mobility pattern prediction is an increasingly important research area, with many open questions yet to be resolved. For example, most existing research studies only the short-time "next place" prediction [24], [25], which would not necessarily be appropriate for the longer-term mobility prediction that is required by CSI prediction (i.e., users' mobility for the whole upcoming month). As this paper does not focus on designing such a long-term mobility prediction algorithm, we currently use a state-of-the-art mobility prediction method based on Poisson distribution (Section VI-A), which is widely applied in previous work, e.g., [6], [15], [16], [26]–[28].

Although CSI prediction and our previous work effSense [5], [6] both leverage heterogeneous networks to save 5G cost in delay-tolerant MCS, the research assumptions and problems are distinct from each other. In effSense, predefine whether a participant has Unlimited and focus on designing data uploading strategies; while in CSI prediction, in addition to uploading strategies, the key technical issue that needs to be addressed is deciding whether to assign a participant to the Unlimited or PAY PER group.

III. EXISTING SYSTEM

In existing, They have used machine learning based on CSI information's.

In existing system to overcome the delay produced by the too much participant in internet access they have applied the scheduling based schemes

In which two plans are allowed in details internet will divide into two types of plans like 2G, 5G ,4G. So that user can decide which plan he can use. By this way overall user count for data access can be reduced.

The solution to this problem is nontrivial, because:

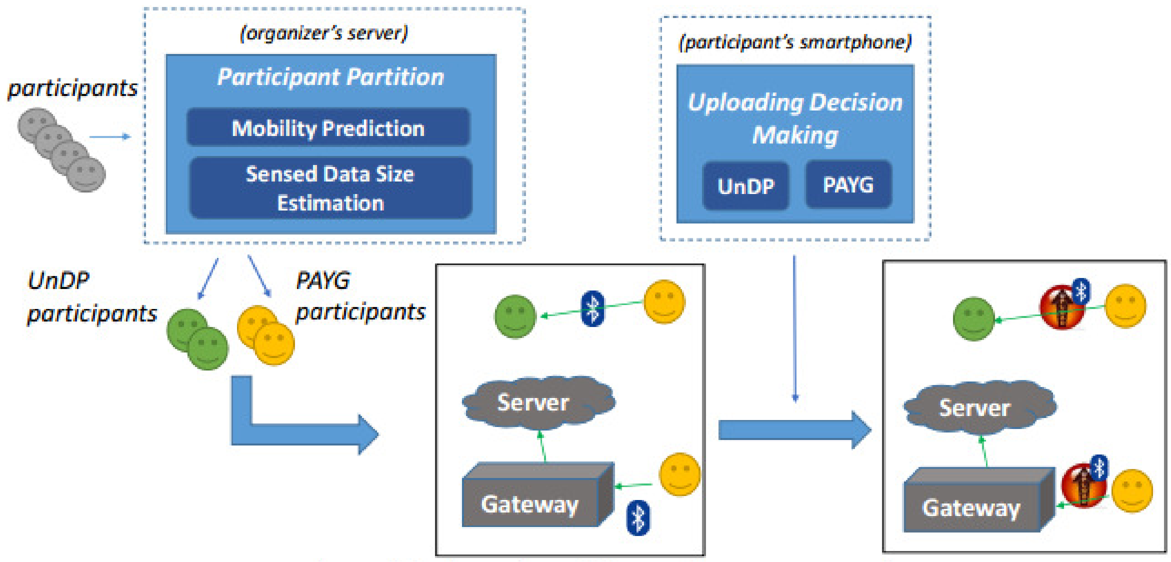
1) It can neither foresee the participants' mobility traces in the next month, nor how much sensed data that needs to be uploaded. Thus, obtaining is not straight- forward: both participant mobility and sensed data size prediction methods should be combined in order to estimate d

2) Different D and P would affect Refunds and RefUnlimited jointly. For example, if P assigns more participants to Unlimited, then Refunds increases and RefUnlimited decreases, so that whether overall Refund increases or decreases remains uncertain. Even if P is determined, D can still impact RefUnlimited, because PAY PER participants hold different uploading strategies under different D.

IV. PROPOSED WORK

To solve the problem formulated in the previous section, we design a novel MCS data uploading framework named CSI prediction. In this section, first use a running example to illustrate the basic idea of CSI prediction and compare it with direct-assignment. Then, give the overview of our proposed CSI prediction framework.

V. BLOCK DIAGRAM



The overview of our CSI prediction framework is shown in Fig.1, which contains two key components.

1) Uploading Decision-Making (Client Component): This component runs on every crowdsensing participant's smart- phone. It is triggered to decide whether to upload/relay or to keep data when a participant encounters a cost-free event, such as meeting another participant or discovering a Bluetooth/WiFi gateway. The uploading decision-making component will be further elaborated in Section.

2) Participant Partition (Server Component): This component runs on the Crowdsensing organizer's server to assign the participants to either the Unlimited or the PAY PER group. It relies on two modules—mobility prediction and sensed data size estimation.

1) Mobility prediction module predicts participants' mobility patterns in the next month. With mobility prediction results, we can forecast how often a participant might meet another participant, a Bluetooth gateway, a WiFi AP, etc.

2) Sensed data size estimation module estimates the amount of sensed data that a specific participant would contribute in the following month. For different participants, sensed data size might vary according to their activeness, privacy concerns, visited locations, etc.

Currently, most telecom operators' 5G data plans can change once a month, so this component needs to run once at the end of a month, to obtain the group partition for the follow- ing month. The participant partition component will be further elaborated in Section VI.

Now we briefly explain CSI prediction's workflow during a crowdsensing task period.

1) As shown in the left part of Fig. 3, before a new month begins, the participant partition component partitions all the participants into two groups with two different 5G refund schemes: a) Unlimited and b) PAY PER.

2) After the new month starts, in each delayed-uploading cycle, when a participant encounters a cost-free event (e.g., encountering a Bluetooth gateway or another participant), the uploading decision-making component decides whether to upload/relay or to keep data. For example, in the right part of Fig., after making the decision, a PAY PER participant relays data to an Unlimited participant via Bluetooth, while another PAY PER participant relays data to a Bluetooth gateway.

3) At the end of each delayed-uploading cycle, CSI prediction checks all the participants to see whether they have nonuploaded data, which can include the sensed data collected by a participant herself and relayed data received from other participants. Then, CSI prediction forces those participants with outstanding nonuploaded data to create 5G connections in order to upload it at the end of the cycle. In fact, only under this condition will PAY PER participants upload sensed data with 5G data cost in a particular cycle.

PARTICIPANT PARTITION

After choosing the uploading strategy for the participants, the crowdsensing organizer also needs to partition the participants into two groups—PAY PER and Unlimited—in order to minimize the 5G data cost that needs to be refunded. To achieve a reasonable participant partition, two factors need to be considered.

1) Mobility Pattern: A participant's mobility pattern affects how often she could meet another participant or a Bluetooth/WiFi gateway.

2) Sensed Data Size: Different participants will most likely contribute different sizes of sensed data due to variant behaviors such as their degree of activity and their privacy concerns.

In this section, we first describe our methods to predict participants' mobility pattern and to estimate participants' sensed data size. Then, we propose a genetic algorithm to partition the participants into Unlimited and PAY PER groups.

VI. CONCLUSION

Refunding MCS participants for additional 5G data price incurred through the crowdsensing process is an efficient marketing strategy meant for the MCS organizer. In this paper, we investigate the problem of how exactly to minimize the total 5G data refund cover the crowdsensing organizer who comes after such a marketing strategy. Established on two trusted 5G price programs, i.e., PAY PER and Unlimited, we propose a delay- tolerant data uploading framework called CSI prediction, whose goal is to minimize the organizer's 5G refund cover all the participants.

By introducing delay-tolerant info uploading mechanisms, Unlimited individuals could relay PAY PER individuals' sensed info to the server without additional 5G cost; PAY PER individuals could also upload their sensed info via free-charge Bluetooth/WiFi gateways to reduce 5G cost. Based on these observations, propose the data uploading approaches for both Shell out PER and Unlimited individuals and design a participant partition algorithm to determine whether a participant ought to be assigned to Give PER or Infinite. The CSI prediction framework was evaluated employing the MIT Reality Mining info set and a larger SWIM simulation info set. The evaluation results revealed that CSI prediction could save up to ~50% of the refund budget in comparison to direct-assignment that assigns each participant to Infinite or PAY PER directly in line with the size of her sensed info.

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