Time Window-Aware Participant Selection Mechanisms in Mobile Crowdsensing: Postprint

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Date: 2018-11-29T00:00:00+00:00

Abstract

Currently, many mobile crowdsensing applications require participants to collect continuous sensing data over a period of time, yet existing research has not adequately considered this aspect. To address the aforementioned application scenario, a time-window-related participant selection mechanism is proposed, which mainly includes a time-window-related participant selection method designed based on dynamic programming algorithm, with the objective of covering the task time period while maximizing data utility; a participant reputation value update mechanism that updates participants' reputation values according to their willingness to participate in tasks and data quality. Finally, through simulation experiments comparing with two widely applied participant selection methods, the experimental results demonstrate that the proposed participant selection mechanism achieves better performance in terms of data reliability, data utility, and sensing cost, thus the proposed participant selection mechanism has better application prospects in time-window-related tasks.

Full Text

Preamble

Vol. 37 No. 1
Application Research of Computers
Accepted Paper

Participant Selection Mechanism for Time Window Dependent Tasks in MCS

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Abstract: Many mobile crowd sensing applications require participants to collect continuous data over a period of time, yet existing research has not adequately addressed this scenario. This paper proposes a time window dependent participant selection mechanism that includes: (a) a participant selection method based on dynamic programming designed to maximize data benefits while covering the task time period; and (b) a participant reputation update mechanism that adjusts reputation values according to participants' willingness to engage and data quality. Simulation experiments comparing the proposed mechanism with two commonly used participant selection methods demonstrate that our approach achieves better performance in data reliability, data benefits, and sensing costs, indicating promising application prospects for time window dependent tasks.

Keywords: mobile crowd sensing; participant selection; continuous data; dynamic programming

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0 Introduction

With the rapid development of smart devices and microelectronics technology, modern smartphones now feature substantial storage capacity and advanced sensors including cameras, temperature sensors, and pedometers [1]. Participants can leverage these sensors to collect environmental data, giving rise to a new sensing paradigm known as mobile crowd sensing (MCS). As illustrated in [Figure 1: see original paper], an MCS network comprises task publishers, a cloud platform, and participants carrying smart devices. Task publishers post tasks on the platform and pay corresponding fees, the platform selects appropriate participants to execute sensing tasks, and participants use their mobile devices to collect and upload sensing data to the cloud platform in exchange for compensation.

MCS networks offer numerous advantages over traditional sensing networks [1] and have found widespread applications in healthcare, environmental monitoring, and transportation [2]-[6]. In practical MCS applications, many tasks demand high data integrity, such as traffic monitoring and noise monitoring. These time window dependent tasks require participants to collect continuous sensing data over a specified duration, posing new challenges for participant selection methods.

Appropriate participant selection is crucial for ensuring efficient and accurate task completion in MCS, making it a focal research area with numerous existing contributions. For instance, reference [7] proposed a reputation-aware data collection mechanism that categorizes participants into direct and indirect data contributors and dynamically updates their reputation values to inform selection. Reference [8] optimized participant selection to minimize the number of selected participants while meeting coverage requirements, thereby reducing task costs. Reference [9] investigated participant selection in peer-to-peer transmission modes. Reference [10] introduced a visual crowd sensing framework called UtiPay that selects participants and data from both macro and micro perspectives. Reference [11] selects appropriate participants based on their historical trajectory data within the sensing region. However, none of these approaches address time window dependent tasks. While reference [12] designed an MST algorithm for such tasks to minimize sensing costs while collecting continuous data, it failed to consider the sensing quality of selected participants.

To address these limitations, this paper proposes an efficient and reasonable participant selection mechanism for time window dependent tasks. We define participant reliability based on two key factors: the participant' s credibility (reputation value) and the volume of sensing data they can provide. Higher reputation values and larger data volumes contribute to greater data reliability. Based on these considerations, we define participant reliability as shown in equation (1).

We introduce a participant selection mechanism for time window dependent tasks (PS-TWDT) comprising two main components: (a) a dynamic programming-based participant selection method that maximizes data benefits while covering all task time windows; and (b) a reputation update mechanism that adjusts participant reputation values based on their willingness to participate and data quality.

1.1 System Model

We assume a task publisher posts a sensing task requiring continuous data collection across N time windows, where L denotes the duration of each time window. The platform has access to a sufficient pool of participants $U = \{u_1, u_2, ..., u_n\}$. Each participant u_i submits a bid b_i^k for time window k, representing their requested compensation. The sensing time interval for participant u_i in time window k is denoted as $[st_i^k, et_i^k]$, where st_i^k is the start time and et_i^k is the end time.

The amount of sensing data participant u_i can provide in time window k, denoted as d_i^k, is primarily determined by the battery level of their smart device [11]. This relationship is modeled by equation (2):

$$d_i^k = f(e_i^k) = \alpha \cdot (e_i^k)^\beta$$

where e_i^k represents the initial battery level of participant u_i' s device when joining time window k, and α and β are parameters of the function relationship, with $\alpha = 8.179$ and $\beta = 0.4633$.

1.2 Defining the Objective Function

In our scenario with sufficient participants, the platform must filter and select appropriate participants for the sensing task. Since the task requires continuous data collection across N time windows, the selected participants' sensing times must continuously cover each time window. To obtain more accurate sensing data, the platform needs to select appropriate participants for each time window, maximizing their reliability while minimizing sensing costs—effectively maximizing the platform' s data benefits.

Each time window' s selection can be formulated as an optimization problem shown in equation (3):

$$\max_{S^k \subseteq U} V^k = \frac{\sum_{u_i \in S^k} r_i^k}{\sum_{u_i \in S^k} b_i^k}$$

Subject to:

$$\bigcup_{u_i \in S^k} [st_i^k, et_i^k] \supseteq T^k$$

where r_i^k represents the data reliability of participant u_i in time window k, b_i^k is their bid, and V^k denotes the data benefit for time window k. Constraint (4) ensures that the union of selected participants' sensing intervals covers the entire task time window T^k.

We define data reliability based on participants' sensing data volume and reputation values. Since MCS nodes are ordinary people with smart devices rather than professionally deployed sensors, the data accuracy varies significantly among participants and directly impacts task outcomes. Therefore, the platform must select participants judiciously to obtain reliable data. Participant reliability depends on two factors: (1) the participant' s credibility (reputation value), where higher reputation yields more reliable data; and (2) the volume of sensing data they can provide, where larger data volumes increase the probability of high-quality data. Based on these considerations, we define participant reliability as shown in equation (1):

$$r_i^k = \theta_i \cdot d_i^k$$

where θ_i represents the reputation value of participant u_i, reflecting their historical task performance, and d_i^k is the amount of sensing data they can provide in time window k.

2 Algorithm Description

The PS-TWDT mechanism aims to ensure continuous coverage of each task time window while maximizing data benefits and compensating selected participants according to their bids. The algorithm pseudocode is presented below, with detailed steps as follows:

Input: Set of users U, initial mobile phone battery levels E, initial credit values R, task duration T
Output: Selected participants S, data benefit V

1. Initialize participant set U with corresponding sensing time windows, bids, phone battery levels, and reputation values.
2. Calculate each participant' s sensing data volume d_i^k and data reliability r_i^k.
3. Sort all participants by their end time et_i^k in non-decreasing order.
4. Use dynamic programming to select the participant set S^k with maximum data benefit.
5. Calculate the data benefit V^k.
6. Compensate participants according to their bids.
7. Return the selected participant set S and data benefit V.

The dynamic programming approach works as follows: For each participant u_i, if their sensing interval starts at the task' s beginning time, they become a candidate starting point. For other participants, the algorithm finds the optimal predecessor participant whose sensing interval ends before the current participant' s interval begins, maximizing the cumulative reliability-to-cost ratio. The solution is built by iteratively selecting participants that maximize the overall data benefit while maintaining continuous coverage.

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3 Reputation Update Mechanism

To more accurately reflect participant credibility, we design a reputation update mechanism that adjusts participants' reputation values after each time window based on their execution performance. Before introducing the update mechanism, we first define the trust status feedback value, which comprises two components: participation willingness degree and data quality.

3.1 Participation Willingness Degree

The participation willingness degree, denoted as w_i^k, measures how actively participant u_i engages in sensing tasks during time window k. As shown in equation (5):

$$w_i^k = \frac{t_i^k}{L} \cdot \frac{e_i^k}{e_{max}}$$

where t_i^k represents the actual time proportion participant u_i spends on sensing tasks in time window k, and e_i^k is their device' s current battery level. A larger time proportion and higher battery level indicate greater participation enthusiasm. This dual-factor approach avoids the bias of single-factor measurement.

3.2 Data Quality

Data quality, denoted as q_i^k, evaluates the sensing data provided by participant u_i in time window k. As defined in equation (6), it comprises four factors: timeliness ε_i^k, completeness η_i^k, accuracy ω_i^k, and value λ_i^k:

$$q_i^k = \frac{\varepsilon_i^k + \eta_i^k + \omega_i^k + \lambda_i^k}{4}$$

These factors are quantified as values in $[0, 1]$, where 0 represents poor quality (untimely, incomplete, inaccurate, worthless) and 1 represents excellent quality (timely, complete, accurate, valuable).

3.3 Trust Status Feedback Value

The trust status feedback value c_i^k is calculated by comparing a participant' s trust status with the average trust status of other selected participants in the task, as shown in equation (7):

$$c_i^k = \log\left(\frac{w_i^k + q_i^k}{2}\right) - \log\left(\frac{\sum_{j\in S^k, j\neq i}(w_j^k + q_j^k)}{2(|S^k| - 1)}\right)$$

A higher willingness degree and data quality yield a higher trust status feedback value, indicating more accurate and reliable task completion. Additionally, trust status is inversely proportional to participant compensation—higher compensation increases data collection costs and reduces platform benefits, resulting in lower trust status feedback values.

3.4 Reputation Value Update

After each time window, the platform updates participants' reputation values based on their trust status feedback values, as defined in equation (8):

$$\theta_i^{new} = \frac{1}{2} + \frac{1}{\pi}\arctan(c_i^k)$$

The updated reputation value will serve as the credibility metric for the participant in the next time window. We quantify reputation values in the range $[0, 1]$, where 0 indicates completely untrustworthy, 0.5 indicates uncertainty, and 1 indicates completely trustworthy. New participants are assigned an initial reputation value of 0.5, representing neutral credibility at the start.

4 Experimental Validation

To validate the effectiveness of the PS-TWDT mechanism, we conducted simulation experiments in MATLAB R2016a. In our scenario, a task publisher requires continuous air quality data collection in a region from 6:00 to 18:00 over ten consecutive days. For each time window, the platform simulates 100 participants with sensing times randomly distributed between 6:00 and 18:00. Participant bids follow a uniform distribution on $[1, 10]$, device battery levels follow a uniform distribution on $[1, 100]$, and the timeliness, completeness, accuracy, and value metrics follow a uniform distribution on $[0, 1]$. After each time window, participant reputation values are updated based on their performance.

We compare PS-TWDT against two commonly used selection methods: MST [12] and random participant selection (Random). The evaluation focuses on three metrics: data reliability, data benefits, and sensing costs.

4.1 Data Reliability

Figure 2 [Figure 2: see original paper] shows the average data reliability per time window, with the y-axis representing the mean reliability of selected participants. PS-TWDT consistently outperforms both MST and Random across all time windows because our algorithm explicitly considers data reliability in the selection process, using dynamic programming to choose participants with the highest reliability in each window. Figure 3 [Figure 3: see original paper] demonstrates the cumulative data reliability over time, where PS-TWDT shows significantly faster accumulation compared to the other two methods.

4.2 Data Benefits

Figure 4 [Figure 4: see original paper] and Figure 5 [Figure 5: see original paper] illustrate data benefit trends as the number of task time windows increases. In Figure 4, the y-axis shows the data benefit per time window. Although PS-TWDT exhibits larger fluctuations, it achieves higher data benefits in every window than MST and Random. This improvement stems from the integrated reputation update mechanism, which ensures that continuously selected participants have higher reputation and reliability values. Combined with the dynamic programming approach that maximizes the ratio of total reliability to total cost, PS-TWDT consistently selects participants with optimal data benefits.

Figure 5 [Figure 5: see original paper] shows the cumulative data benefit over time. As the number of executed time windows increases, PS-TWDT' s cumulative benefit grows at a markedly faster rate than the other methods, with the performance gap widening over time.

4.3 Average Cost

Figure 6 [Figure 6: see original paper] presents the average data cost per time window. PS-TWDT achieves costs comparable to MST and significantly lower than Random. Both PS-TWDT and MST employ dynamic programming algorithms that consider participant bids during selection, whereas Random ignores cost factors, resulting in higher and more volatile expenses.

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5 Conclusion

This paper addresses the participant selection problem for time window dependent tasks in mobile crowd sensing by proposing the PS-TWDT mechanism. Our approach incorporates participant-specific factors into the selection process and introduces a reputation update mechanism that dynamically adjusts reputation values after each task execution. Experimental results demonstrate that PS-TWDT enhances data reliability and benefits while controlling sensing costs, making it well-suited for time window dependent MCS applications.

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Note: Figure translations are in progress. See original paper for figures.