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A Survey on Mobile crowd sensing using MCS task allocation & incentives

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Abstract:

This paper first defines a novel spatial-temporal coverage metric, k-depth coverage, for mobile crowd sensing (MCS) quandaries. This metric considers both the fraction of subareas covered by sensor readings and the number of sensor readings amassed in each covered subarea. Then iCrowd, a generic MCS task allocation framework operating with the energy-efficient Piggyback Crowdsensing task model, is proposed to optimize the MCS task allocation with different incentives and k-depth coverage objectives constraints. iCrowd first prognosticates the call and mobility of mobile users predicated on their historical records, then it culls a set of users in each sensing cycle for sensing task participation, so that the resulting solution achieves two dual optimal MCS data amassment goals—i.e., Goal. 1 near-maximal k-depth coverage without exceeding a given incentive budget or Goal. 2 near-minimal incentive payment while meeting a predefined k-depth coverage goal. We evaluated iCrowd extensively utilizing an immensely colossal-scale authentic-world dataset for these two data accumulation goals. The results show that: for Goal.1, iCrowd significantly outperformed three baseline approaches by achieving 3-60 percent higher k-depth coverage; for Goal.2, iCrowd required 10.0-73.5 percent less incentives compared to three baselines under the same k-depth coverage constraint.

Index terms: - Mobile crowd sensing (MCS), MCS task allocation, incentives.

1. INTRODUCTION

With the rapid proliferation of sensor-equipped perspicacious-phones, Mobile Crowd-sensing (MCS) [3] has become an efficient way to sense and accumulate environment data o urban area in authentic-time (e.g., air quality, temperature or noise level). In lieu of deploying static and extravagant sensor network in urban area, MCS leverages the sensors embedded in mobile phones and the mobility of mobile users to sense their circumventions, and utilizes the subsisting communication infrastructure (e.g., 3G, Wi-Fi etc.) to accumulate data from mobile phones scattered in the urban area. By amassing sensor readings from mobile users, a "big picture" of the environment in the target area can be obtained utilizing MCS without paramount cost. We propose to study a novel MCS task allocation quandary for Piggyback Crowd sensing applications, where we first surmise that each MCS participant senses and uploads sensor readings leveraging smartphone opportunities (e.g., placing a 3G call) to reduce the MCS energy consumption. We then make following posits regarding the spatial temporal coverage and incentive: k - depth coverage of MCS tasks. While the subsisting spatial temporal coverage metrics customarily postulate that the environment data (e.g., air quality) of a subarea in a sensing cycle could be represented by a single sensor reading, it is plausible to believe that the each subarea could be better characterized if we could deduce the environment characteristics utilizing multiple sensor readings amassed from the same subarea. However, if we increment the number of sensor readings in a subarea above a certain threshold, the precision of the deduced value may not increment anymore [10]. Thus we propose a novel spatial-temporal coverage metrics–i.e., k depth coverage, which could be utilized as either an objective or a constraint of MCS data amassment In this section, we formulate the task allocation quandary and present the iCrowd framework in detail. Categorically, a generic optimization quandary for MCS task allocation is introduced to meet two dual MCS data amassment goals; then iCrowd–a coalesced task allocation framework for achieving both goals—is presented We formulate the task allocation quandary and present the iCrowd framework in detail. Concretely, a generic optimization quandary for MCS task allocation is introduced to meet two dual MCS data amassment goals; then iCrowd–a amalgamated task allocation framework for achieving both goals—is presented.

2. RELATED WORK

Subsisting system

MCS leverages the sensors embedded in mobile phones and the mobility of mobile users to sense their circumventions, and utilizes the subsisting communication infrastructure (e.g., 3G, Wi-Fi etc.) to amass data from mobile phones scattered in the urban area. By amassing sensor readings from mobile users, a "big picture" of the environment in the target area can be obtained utilizing MCS without paramount cost.

Disadvantages

1. Budget utilization is high.
2. Cost is not consequential.

Proposed system

We present iCrowd—a near-optimal task allocation framework for mobile crowd sensing, which can amend the efficiency of environment data amassment with less cost. Here we first discuss the motivations and background of our MCS research, then we formulate an incipient MCS research quandary with a cumulated set of research posits and objectives. We elaborate the technical challenges of the proposed research and determinately we summarize our technical contributions.

Advantages

1. **Reduce the energy consumption.**
2. **Control the overall incentive cost.**

Contributions

We formulated the quandary of optimal task allocation in piggyback crowd sensing subject to sundry spatial-temporal coverage and incentive objectives constraints, with a novel spatial-temporal coverage metric and a flexible incentive model. To the best of our erudition, this is the first cumulated framework addressing the task allocation issue in the context of PCS, two dual research objectives are targeted in a amalgamated manner, leveraging the presaged call/mobility patterns and call opportunities of the participants to sense and upload data in the MCS task. In order to achieve both MCS data accumulation goals, we proposed a two-phase task allocation framework denominated iCrowd. It takes a novel approach to probe utilizer-cycle cumulation set, which can achieve either 1) near-maximal k-depth coverage objective under the budget constraint, or 2) near-minimal overall incentive payment under the k-depth coverage constraint. Theoretical analysis shows that the proposed search algorithm can achieve the near-optimality with low computational intricacy. We evaluated our proposed algorithms with the authentic world dataset D4D [9], which contains 4-month call records of 50,000 users from Cote d'Ivoire. We show that the proposed framework performed better than three baseline approaches, utilizing the call records of two separate regions in Abidjan. Concretely, iCrowd achieved 3.0-60 percent higher k-depth coverage on average than the baseline approaches, under the same budget constraint, for Goal. 1 and it additionally consumed 10.0 - 73.5 percent less overall incentive compared to three baselines under the same k-depth coverage constraint for Goal.

3. IMPLEMENTATION

Icrowd system overview

We formulate the task allocation quandary and present the iCrowd framework in detail. Concretely, a generic optimization quandary for MCS task allocation is introduced to meet two dual MCS data accumulation goals; then iCrowd–a coalesced task allocation framework for achieving both goals—is presented.

Task allocation quandary in icrowd

Given a set of volunteer mobile users, the target region divided by a set of subareas (e.g, cell towers in our study), and the MCS process consisting of a sequence of equal length sensing cycles (e.g., one cycle per hour), the task allocation quandary of iCrowd is to cull a number of participants from the volunteer mobile users and to determine in which sensing cycles each culled participant is assigned the PCS task, subject to sundry optimal MCS data accumulation goals.

Design of icrowd

iCrowd follows a centralized task allocation approach, where a central server amasses and stores the volunteering mobile users' historical call traces in the target area, and the server culls participants from all volunteering users nd assigns tasks to each participant in a set of sensing cycles. afore the PCS task execution. Only culled participants are needed to perform sensing tasks, and each culled participant returns sensor readings only in the assigned sensing cycles when a phone call is made. In order to solve the above task allocation quandary, iCrowd employs a two-phase solution. In Phase 1, it soothsays each user's call/mobility in the study period, utilizing the historical call and mobility traces of all users. In Phase 2, it incrementally culls participants and assigns sensing tasks to each participant in different sensing cycles predicated on the presage results, the estimated k-depth coverage and incentive cost.

Call/mobility presage

Surmising the call sequence follows an inhomogeneous Poisson process , the probability of a utilizer u to place at least

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one phone call at cell tower . Which is estimated as the average number of calls that u has placed at t in the historical traces corresponding to the sensing cycle i?

Utility calculation

We now describe two types of utility functions Utility1 and Utilityn (n _ 2). Utility1 is utilized for the first iteration of the Iterative Avaricious Process, and an incipient utility function Utilityn (n _ 2) is engendered for each consecutive iteration. The Utility1 Calculation – Given the set of incrementally culled utilizer-cycle cumulations X1 in the first iteration of Iterative Cupidinous Process (X1 ¼ ; for initialization the avaricious search process).

Performance analysis

We present the theoretical analysis of iCrowd in terms of approximation ratio and computational intricacy for optimal MCS data accumulation Goal. 1 and Goal. 2, respectively. Performance for Goal. 1 – According to the theory of sub modular function maximization under the sub modular knapsack constraint, iCrowd can ensure a Near-Optimal solution with ða; 1 _ e_1Þ-approximation bound when maximizing kCovðXÞ with the given budget. For example, given the Base/Bonus incentive settings ba ¼ $50 and bo ¼ $1, supposing with $10,000 budget the optimal solution obtained by the brute-force enumeration algorithm achieves the total coverage quality of 1,000 in prospect, then iCrowd with $10000 _ 50þ1 50 ¼ $10200 budget can achieve at least a coverage quality of 630. Performance for Goal. 2 – Considering the duality of the submodular maximization/minimization quandaries between Goal. 1 and Goal. 2, we could facilely conclude that iCrowd could achieve near-optimality in minimizing the overall incentive payment under k-depth coverage constraint, utilizing our conclusion made for Goal. 1. For detailed discussion on the duality between the optimization quandaries of Goal. 1 and Goal. 2, please refer to.

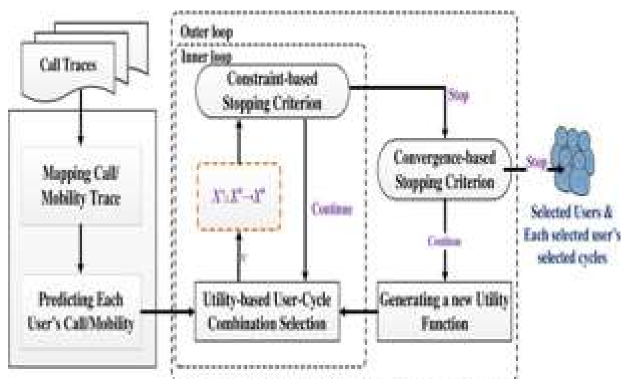

Fig:-1 System Architecture

4. EXPERIMENTAL RESULTS

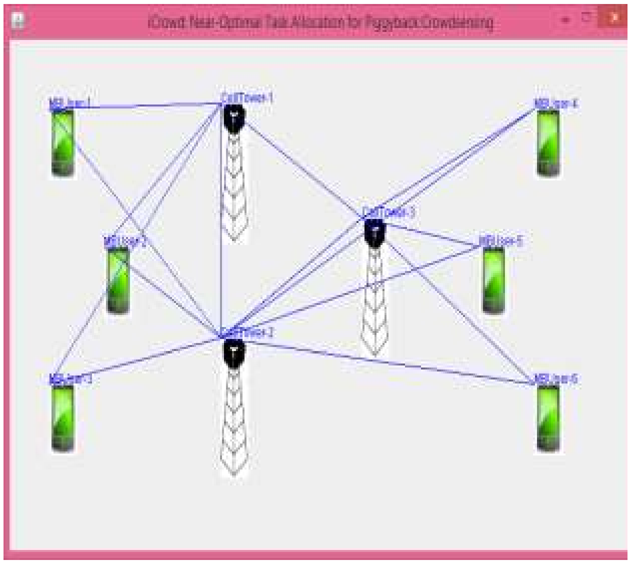

Fig:-2 System Network

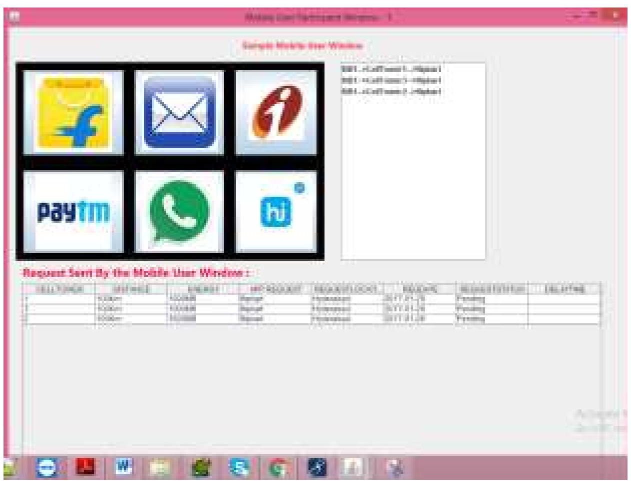

Fig:-3 Mobile User

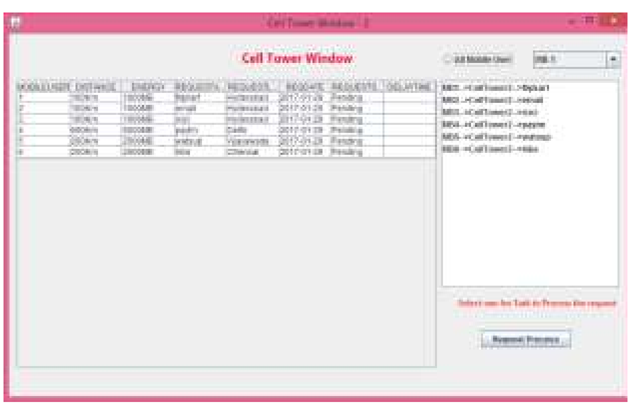

Fig:-4 Request Process

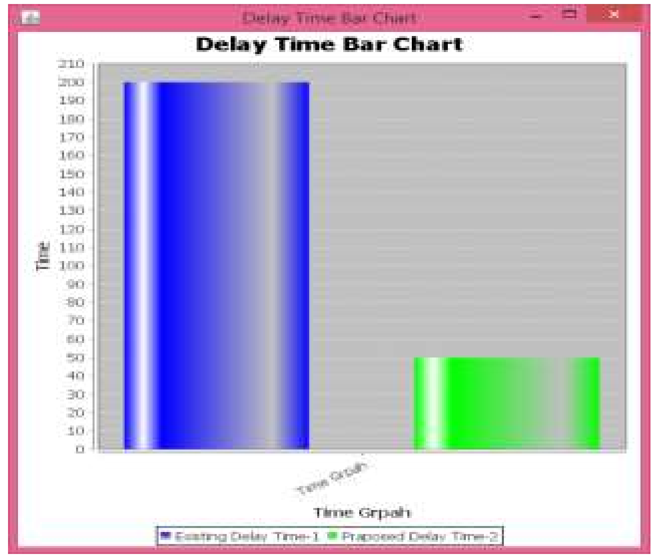

Fig:-5 Delay Time Graph

5. CONCLUSION

In this paper, we proposed a coalesced task allocation framework, iCrowd, for Piggyback Crowdsensing (PCS). iCrowd is designed to optimally allocate sensing tasks to PCS participants, subject to different incentive and spatial-temporal coverage constraints/objectives. Categorically, iCrowd could be adopted to either maximize the overall k-depth coverage across all sensing cycles with a fine-tuned budget or to minimize the overall incentive payment while ascertaining a predefined k-depth coverage constraint, by culling a number of participants and determining in which sensing cycles each culled participant is needed for the PCS task participation. The PCS was adopted to reduce energy consumption of individual mobile contrivance, by exploiting call opportunities to perform sensing tasks and upload sensed data. In order to allocate PCS task for either optimal MCS data accumulation goals, iCrowd first presages the coverage probability of each mobile utilizer, then performs a near-optimal participant/cycle task allocation search algorithm with low computational intricacy. Theoretical analysis proves that iCrowd can achieve near-optimality for both optimal MCS data accumulation goals, and evaluations with an immensely colossal-scale realworld dataset show that iCrowd outperformed six baseline approaches. For Goal. 1 it achieved 3%–60% higher k-depth coverage compared to baseline approaches under the same budget constraint, while for Goal. 2 iCrowd required 10.0% − 73.5% less overall incentive compared to baselines under the same k-depth coverage constraint

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