Task Assignment in Mobile Crowdsensing: Present and Future Directions

Wei Gong, Baoxian Zhang, Cheng Li

Abstract

Mobile crowdsensing has wide application perspectives and tremendous advantages over traditional sensor networks due to its low cost, extensive coverage, and high sensing accuracy properties. Task assignment is a crucial issue in mobile crowdsensing systems which is intended to achieve a good tradeoff between task quality and task cost. The design of efficient task assignment mechanisms has attracted a lot of attention and much work has been carried out. In this article, we present a comprehensive survey of state-of-the-art task assignment mechanisms in mobile crowdsensing systems. We will first introduce several fundamental issues in task assignment and classify existing mechanisms based on different design criteria. Then we introduce how each of the existing mechanisms works and discuss their merits and deficiencies. Finally, we discuss challenging issues and point out some future directions in this area.

Introduction

Mobile crowdsensing is a new sensing paradigm that exploits the ubiquity of crowds who carry smart devices to collect sensing data. Mobile crowdsensing has many advantages over traditional sensor networks due to its low cost, extensive coverage, and high sensing accuracy properties. Mobile crowdsensing has a wide range of application scenarios such as environmental monitoring [1, 2], healthcare [3], smart cities [4, 5], and intelligent transportation systems. A mobile crowdsensing system typically consists of a service platform, a set of task requesters, and a set of data collectors. Task requesters publish a set of tasks on the service platform. The specifications of tasks include task location, task duration, data accuracy requirement, data collection times, task budget, and other requirements. The service platform determines how to assign tasks to suitable data collectors for some goals. Data collectors accept a set of tasks, collect required sensing data, return their sensing results and receive compensation for their involvement. In the rest of this article, without causing confusion, we shall use the terms "data collectors," "mobile users," and "workers" interchangeably.

Task assignment is a crucial issue in the design of mobile crowdsensing systems. In general, tasks are expected to be assigned to proper data collectors to achieve the maximum overall task quality subject to given cost/budget constraints or minimum costs subject to given task quality requirements. There are many factors affecting task quality, including the amount of collected sensing data, task duration, and task spatiotemporal coverage. A higher amount of sensing data collected often means increased task quality. Balanced task spatiotemporal coverage typically means higher task quality. There are also many factors that impact task cost, including worker recruitment cost, worker travel cost, and data transferring cost. Worker recruitment cost can be per-worker based, or per-data-collection based, or both. Data transferring cost is the communication cost generated when workers have to upload sensing results via cellular networks or other networks that charge fees.

In this article, we present a survey of state-of-the-art task assignment mechanisms in mobile crowdsensing. Among the existing work, the authors in [6-10] focus on participatory sensing in which case task assignment is mainly aimed to schedule workers' moving paths to improve task quality under each worker's travel cost budget. The authors in [1, 2, 4, 11–15] focus on opportunistic sensing in which case data collectors acquire sensing data along their paths and their daily routines are not disturbed. Among the opportunistic sensing mechanisms, the authors in [1, 4, 11] focus on selecting proper workers to achieve maximum task coverage quality by considering workers' moving behavior. The authors in [2, 12–15] focus on maximally taking advantage of both communication opportunity for data exchanging/uploading and worker moving behavior for achieving optimized task coverage quality.

The reminder of this article is structured as follows. In the following section, we introduce some fundamental issues in task assignment and classify existing mechanisms based on different criteria. Then we discuss how each of the existing mechanisms work and discuss their advantages and disadvantages. Following that, we discuss challenging issues and point out some future directions in this area.

Fundamental Issues and Mechanism Classification

In this section, we first introduce fundamental issues for task assignment in mobile crowdsensing and then divide existing task assignment mechanisms by using different criteria.

Fundamental Issues

There are two fundamental issues for task assignment in mobile crowdsensing: task quality and task cost. Most task assignment mechanisms are designed to achieve a good tradeoff between task quality and task cost. In the following, we introduce these two issues.

Digital Object Identifier:
10.1109/MNET.2018.1700331

Wei Gong and Baoxian Zhang (corresponding author) are with the University of Chinese Academy of Sciences; Cheng Li is with Memorial University.

Task Quality

Improving task quality is the most important design objective for a majority of crowdsensing systems. There are several factors having a major impact on task quality, including data collection times, task duration, and task spatial-temporal coverage.

Data collection times refer to the number of times a target phenomenon is expected to be sensed. On one hand, multiple measurements can reduce sensor reading errors and make sensing results approach the ground truth. On the other hand, there are tiny fluctuations of sensing data even in short durations and small areas. Therefore, in most cases, multiple measurements are necessary to improve data quality. In [8, 9], data quality keeps increasing as the collection times increase, which is characterized by a non-decreasing submodular function. In contrast, in [11, 15], when the number of collected data exceeds certain threshold, data quality will not increase any more.

Task duration is the time period from the instant a task is published to the deadline of the task. In most cases (e.g., [1, 8, 9]), tasks cannot be performed after their deadlines. In [10], a soft deadline is used, which means that task quality is decreased instead of dropping to zero after the deadline. For this case, a punishment function is constructed for measuring the degradation in task quality. The authors in [12] use minimum average makespan and minimum largest makespan to characterize task quality where task makespan is the time period from when a task is published to the time the task result is returned to the task requester in a mobile social network where only short-range wireless communications between mobile users are available.

Task spatiotemporal coverage is another important metric to evaluate task quality. In most scenarios, crowdsensing systems select a set of workers to perform sensing tasks that are scattered in many time periods and many places. These workers typically move subject to moving budgets (for participatory sensing) or along their own paths (for opportunistic sensing). In many cases, not all tasks can be performed all the time due to such restriction on workers' movements. Therefore, a spatial-temporal coverage ratio of tasks is often used as a key metric to evaluate task quality.

Task Costs

Task costs are the costs paid to perform tasks, including worker recruitment cost, worker travel cost, and data transferring cost. The first is paid by the service platform to recruited workers for their involvement; the latter two are paid by workers for their movements for data collection and data uploading using pay-feeing networks, respectively.

Worker recruitment cost includes per-worker recruitment cost and per-data collection cost. Per-worker recruitment cost is paid to each worker as long as the worker is recruited into the crowdsensing system. Per-data collection cost is paid to a worker once they collect the requested sensing data at a given time period and given task location.

Worker travel cost is the travel compensation for workers if they need to take extra movement [6–7] or change their paths [8] to perform tasks. In [6–7], workers are recruited to move to task locations from their initial locations for task processing. In [8], each worker can make a detour on the way from their initial location to the destination to perform sensing task(s) at certain locations.

Task costs are the costs paid to perform tasks, including worker recruitment cost, worker travel cost, and data transferring cost. The first is paid by the service platform to recruited workers for their involvement; the latter two are paid by workers for their movements for data collection and data uploading using pay-feeing networks, respectively.

Data transferring cost is the data transmission cost generated for uploading sensing data. Sensing data can be uploaded to task requesters in several ways. First, sensing data can be sent to task requesters via cellular networks [13] in real time at large expense. Second, sensing data can be sent to task requesters via WiFi access points (APs) when such service is available, which is typically free of charge but causes significant delay. In this aspect, the authors in [14] adopt WiFi APs for data uploading but allow multi-hop forwarding for such a purpose. Third, task results can be sent back to the task requester directly via short-range communications (e.g., Bluetooth, WiFi, etc.) without causing data transfer costs when the task executor and the requester meet each other (e.g., [12]).

Mechanism Classification

Existing task assignment mechanisms in mobile crowdsensing can be divided into different categories by using different criteria.

Participatory-Sensing-Based Task Assignment/Opportunistic-Sensing-Based Task Assignment: According to whether a crowdsensing system needs deep human involvement, task assignment mechanisms can be categorized into two types: participatory-sensing-based and opportunistic-sensing-based. In participatory sensing [6–10], workers consciously move to specific task locations to perform tasks following task requesters' willingness. The service platform schedules the workers' moving paths to traverse some task locations to perform tasks. Each time a task is performed, valuable sensing data are acquired and thus task quality is improved. The main task cost in this approach is worker travel costs. The focus of designing this type of mechanism is how to schedule workers' paths so as to maximize task quality under worker travel cost constraints. In opportunistic sensing [1, 2, 4, 11–15], the tasks are performed fully unconsciously by the workers such that the moving behaviors of the workers are not disturbed. Data collectors move along fixed paths or randomly but following their daily mobility patterns. When a worker enters a task area, the task in this area is said to be covered by the worker. The focus of this type of mechanism is how to select proper workers to maximize task quality by considering worker moving behavior [1, 4, 11], or both worker moving behavior and communication opportunity distribution [2, 12–15].

Online Task Assignment/Offline Task Assignment: According to the knowledge available to the service platform, task assignment mechanisms can be divided into online task assignment mechanisms and offline task assignment mechanisms. In online task assignment [1, 2, 8, 9, 12], the service platform has knowledge only of ongoing tasks and already-arrived workers. In this scenario, workers arrive and leave based on their own

Offline task assignment solutions can achieve much better performance than online task assignment solutions since they have more information about tasks and workers. In contrast, online task assignment is more flexible and suitable for dynamic real-world situations.

schedules. Each time a worker arrives, the service platform can assign a set of tasks to this worker based on the ongoing tasks and worker mobility knowledge. In offline task assignment [1, 4, 6, 7, 10, 11, 13–15], the service platform has full knowledge of all tasks and workers and it makes a full task assignment schedule at the beginning, and all workers perform tasks following this schedule. Offline task assignment solutions can achieve much better performance than online task assignment solutions since they have more information about tasks and workers. In contrast, online task assignment is more flexible and suitable for dynamic real-world situations where global state information is difficult to gather in advance and also subject to frequent unexpected changes.

PoIs-Based Task Assignment/Full-Area Based Task Assignment: According to the spatial distribution of crowdsensing tasks, task assignment mechanisms can be categorized into PoIs-based (Points of Interest based) task assignment mechanisms and full-area based task assignment mechanisms. In PoIs-based task assignment mechanisms [1, 4, 6–10, 13, 14], workers can perform tasks only when they are in the sensing ranges of PoIs. In PoIs-based mechanisms using participatory sensing, the service platform decides which tasks to be performed and in what order for every worker. In PoIs-based mechanisms using opportunistic sensing, the service platform decides how to select workers to maximize the number of tasks to be performed or obtain maximum overall task quality. In full-area based task assignment mechanisms [2, 11, 15], tasks are expected to be performed in every sub-area and every cycle. The service platform typically attempts to maximize the spatiotemporal coverage ratio of all tasks.

Survey of State-of-the-Art Task Assignment Mechanisms

In this section, we present a survey of the state-of-the-art task assignment mechanisms for mobile crowdsensing. We first survey participatory-sensing-based mechanisms and then opportunistic-sensing-based mechanisms. We introduce how each of these mechanisms works and discuss their advantages and disadvantages.

Participatory Sensing Mechanisms

First we introduce five participatory sensing mechanisms for mobile crowdsensing. Among the existing mechanisms, the authors in [6, 7, 10] proposed offline mechanisms, while those in [8–9] proposed online mechanisms. The authors in [6–7] do not consider task deadlines, while those in [8–9] consider hard task deadlines, and those in [10] consider soft task deadlines.

Local Ratio Based Algorithm (LRBA): The work in [6] is an approximation algorithm for maximizing the rewards of the service platform. The algorithm aims to maximize the total profits of service platform with budget constraints. LRBA assumes that each task has a specific location, and workers have to move to the exact location to accomplish it. Each task needs to be accomplished by a sufficient number of workers to ensure the required sensing quality. Each worker travels from their initial location to several task locations under a travel distance budget. For each accomplished task, workers are paid from the platform and the platform receives earnings from the task requesters. Based on the above assumptions, the service platform assigns workers to complete a set of tasks to maximize its profits. The platform's profits are the earnings from the task requesters minus the payments to the workers. The authors proved this problem is NP hard and used a local ratio theorem to decompose the problem into sub-problems of single users. Then they defined a new reward function and solved the sub-problem of each worker in an iterative way. Finally, they made the task schedule in reverse order. The authors also proposed a pricing mechanism of payments from the service platform to the workers. They assume that the willingness of a worker accepting a task depends on the ratio of the current reward to the maximum possible reward. They determine the payment to the workers by maximizing the product of the expected reward of the platform and workers according to bargaining theory. A disadvantage of LRBA is that it does not consider the timeliness of workers and tasks since timeliness is an important property in many crowdsensing systems.

Minimum Cost Maximum Flow (MCMF): The work in [7] is targeted for the FPMT (few participants, more tasks) problem in mobile crowdsensing. Each worker is required to complete exactly q tasks and each task is required to be performed by p workers. MCMF aims to maximize the number of tasks accomplished and minimize the total travel distance of all workers simultaneously. The authors transformed this problem into a minimum cost maximum flow problem where the number of tasks accomplished represents the flow and travel distance represents the cost. As illustrated in Fig. 1, the flow network is modeled as a three-level directed graph from source to sink. The first-level nodes represent m workers. Since each worker exactly takes q tasks, the capacity of the edge between source and worker is q. The second-level contains C_q^n task sets. The capacity of an edge between a first-level node and a second-level node is also q,and its associated cost is the shortest travel distance that the worker needs to traverse every task in their selected task set. The third-level contains a number of n tasks. The capacity of the edge between a second-level node and a third-level node is one if the selected task set contains the task. The capacity of the edge between a third-level node and the sink is p since each task is required to be performed by p workers. The algorithm keeps selecting an augmenting path with minimum cost when there still exists an augmenting path in the residual network. The complexity of the algorithm is shown to be exponential since there exist too many combinations for task sets. To tackle this issue, the authors presented a heuristic solution to reduce the computational complexity by restricting each worker to choose tasks from their nearest k ($k \geq q$) tasks instead of from all tasks.

Quality-Aware Online Task Assignment (QAOTA): This algorithm [8] is an online task assignment algorithm for a location-based crowdsensing system. In such a system, tasks and workers arrive sequentially. Each task has a specific location, a starting time, and an expiration time. A task can be performed by multiple workers. Each worker is with an arriving time, an initial location, a destination, a travel cost budget, and a capacity (maximum number of tasks they can perform). Workers move among task locations to perform tasks. After completing a task, a worker will get a reward. The reward for performing a task is a non-decreasing and submodular function. The work in [8] aims to maximize the total rewards of all tasks under given travel and capacity budgets. To address the problem, the authors proposed the QAOTA algorithm, which uses branch and bound to allocate tasks to each new arriving worker. The authors proved that QAOTA is competitive with the offline optimal solution.[1]

Quality/Progress based Algorithm (QPA) and Task Density based Algorithm (TDA): The algorithms in [9] are also online task assignment algorithms for location-based crowdsensing systems. Different from the QAOTA algorithm proposed in [8], QPA and TDA do not put restrictions on the maximum task number for a user to perform. In [9], the authors aimed to maximize the total rewards of all tasks under given travel budgets. For this purpose, they proposed two online greedy heuristic algorithms, both of which work in a hop by hop manner for task selection. The QPA algorithm uses the ratio of task quality increment and travel cost as a measure for task selection. In contrast, the TDA algorithm uses task spatial density as a measure for task selection. In TDA, workers are more likely to be guided to regions with high task spatial densities. Simulation results show that the performance of QPA and TDA is better than QAOTA under equivalent computation resources.

Hybrid Genetic Algorithm (HGA): The algorithm in [10] is designed for task assignment in crowdsensing systems with spatial-temporal coverage requirements. In [10], each task is with an initial time, a processing time, an expiration time, and a specific location. Each task needs to be performed exactly once. A task can be performed after its expiration time but with a penalty cost that depends on how long the task tardiness is. All workers are available all the time but have different initial locations. The algorithm in [10] aims at minimizing the sum of penalty costs of all tasks by scheduling the moving paths of workers. The authors first proposed an earliest-completion-time-first (ECT) heuristic algorithm in which the task with the earliest deadline has the highest priority to be performed. Then the authors proposed the HGA algorithm, which uses ECT as the initial solution. In HGA, a chromosome contains multiple task genes and worker genes. By continually crossing over different chromosomes and mutating new chromosomes, the algorithm terminates when the generation number exceeds a given threshold or the standard deviation of the fitness values of the chromosomes is small enough. Simulation results show that HGA offers better performance than some greedy algorithms.

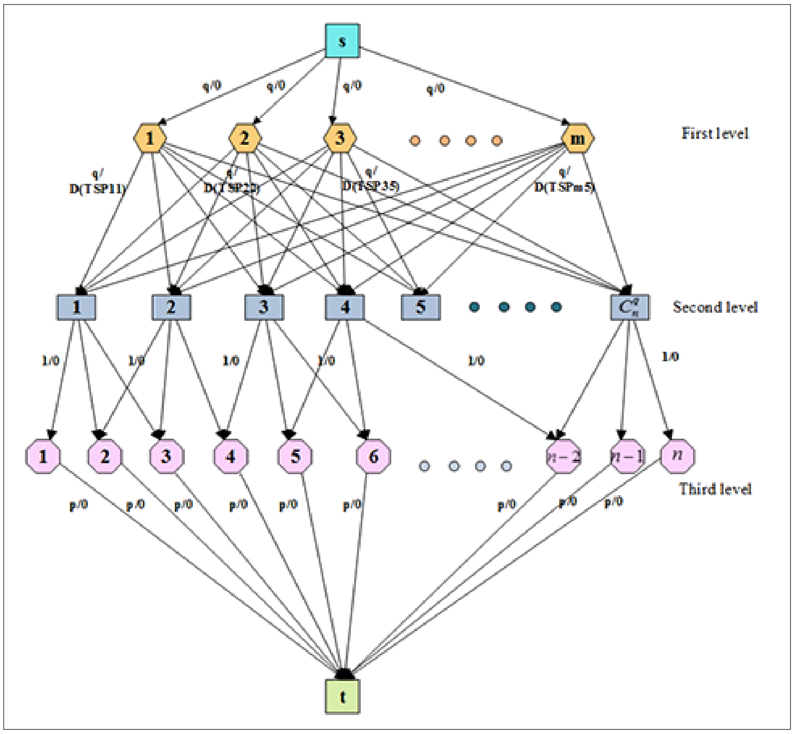

FIGURE 1. Illustration of how minimum cost maximum flow works for worker selection in MCMF [7]. The values "x/y" besides each edge means its link capacity is x and its cost (travel cost) is y. D(TSPuv) means the travel cost for worker u to cover all tasks in task set v.

Opportunistic Sensing Mechanisms

Next, we will introduce eight typical opportunistic sensing mechanisms. Among these mechanisms, [1, 4, 11] focus on selecting proper workers to achieve maximum task coverage quality by considering workers' moving behavior. The authors in [11] consider mobility prediction based on daily mobility patterns, while [1, 4] consider a fixed trajectory for each worker. The authors in [2, 12–15] focus on maximally taking advantage of available communication opportunities and worker moving behavior for achieving improved task quality, where [12] utilizes direct data exchange opportunities among mobile users, [13, 14] focus on data uploading to fixed infrastructure via data offloading [13] or multi-hop forwarding [14], and [2, 15] focus on data uploading piggybacked with 3G phone calls. Regarding mobility behavior, all mechanisms in [2, 12–15] utilize worker mobility patterns derived using workers' daily trajectories.

Moving-Behavior-Based Mechanisms

Dynamic Participant Selection (DPS): The approach in [11] is a multitask-oriented worker selection strategy to meet the quality-of-information (QoI) requirements of multiple simultaneous tasks subject to different budget constraints. In [11], the task region is divided into several sub-regions and the time period is equally divided into multiple time slots. Each spatiotemporal block refers to a sub-region in a time slot. Each task publisher provides a sensing task covering all the spatiotemporal blocks such that a required amount of sensing data is expected to be collected in each spatiotemporal block. Each task publisher has an incentive budget to reward workers. Workers move in the task region to collect sensing data

[1] In [7], the authors built an auxiliary function to replace the original non-monotonic task quality function, which greatly eases the algorithm implementation. The approximation ratio of QAOTA is derived between the result by the new auxiliary function and that by the original quality function.

Existing work has focused on either opportunistic sensing or participatory sensing individually. However, such an approach to task assignment may either lead to unsatisfactory task quality (for the former) or high cost (for the latter).

on their path. Each worker gets a payment for their engagement. The crowdsensing system aims to select a set of workers to maximize the total QoI utility of all tasks with given incentive budget constraints. The QoI utility measures the difference between the wanted data amount and the collected data amount in every spatiotemporal block and chooses the Frobenius norm to normalize the spatiotemporal data matrix. To solve this problem, the authors first transformed this multi-objective optimization problem into a single-objective optimization problem by using weighted-sum strategy. Then they proposed a greedy algorithm to select workers, one for each time. In each round, the algorithm selects the most promising worker who has the largest utility enhancement over their payment after this worker's involvement. The authors further used workers' historical trajectories for mobility prediction to further improve performance.

Quality-Aware Coverage Mechanism under Incentive Constraints (QAI): This approach was proposed in [4]. In [4], different PoIs (e.g., cafes, shopping malls, and offices) are associated with different weighted values, which characterize the importance of each of these places to visit. A PoI is said to be covered by a worker if the PoI is in the sensing range of the worker's path. The coverage quality by a worker on a PoI is the weighted value of this PoI if the PoI is covered by the worker and 0 otherwise. The coverage quality of a PoI is the sum of the coverage quality of all workers visiting this PoI. Each worker is associated with an incentive cost. The objective of this work is to select a set of workers to maximize the total coverage quality of all PoIs while the sum of the incentive costs of all selected workers is below a given budget constraint. To solve this problem, an approximation algorithm was proposed that selects a new worker who leads to the maximum ratio of the coverage quality increment and incentive cost in each round. The algorithm keeps running until no more workers can be selected without causing an incentive budget violation. The approximation ratio of the algorithm is proved to be $1 - 1/e$ and simulation results show that the algorithm is near optimal.

Real-Time Task Assignment in Spatial Crowdsensing (RSC): The aim in [1] is to maximize the number of covered tasks while the number of selected workers cannot exceed a certain budget. In [1], each task has a location, a sensing range, a starting time, and a deadline. A worker is with an initial location and moves around to collect sensing data. When a worker is in the sensing range of a task, this task is said to be covered by the worker. In [1], time is divided into multiple periods and based on the allowed flexibility of the budget adjusting in each time period, the maximum task coverage problem can be transformed into two different problems: fixed budgets and dynamic budgets. Fixed budget means that the maximum number of selected workers for each time period is fixed. For this problem, the authors presented three heuristics, all of which select workers in a one-by-one manner. Among them, the basic heuristic always selects the worker covering the maximum uncovered tasks, the temporal heuristic selects the worker covering a set of tasks such that the sum of the reciprocal of their remaining completion times is the maximum, and the spatial heuristic chooses the worker covering a set of tasks such that the sum of the reciprocal of their location entropies is the maximum. Here, location entropy is a measure reflecting the popularity of a task location being visited in the long term. Dynamic budgets means that the number of workers recruited in different time periods can be adjusted. An adaptive algorithm was proposed considering the current budget utilization status and also the gain of choosing the current worker.

Moving-Behavior-&-Communication-Opportunity-Based Mechanisms

Average Makespan Sensitive Online Task Assignment (AOTA): The approach in [12] is designed for mobile social networks. In this scenario, a task requester and several workers are moving around in the same space. The task requester can communicate with workers using short-range communication when they encounter. The inter-meeting time between task requester and workers follows exponential distribution. The task requester decides whether to assign a task to a worker when they meet. Each task has a sensing time that follows a uniform distribution. When the task requester meets the worker again, the worker can return the results to the requester. The makespan of a task is the time duration from the time assigning the task to the time receiving the task result. Then the authors defined the following problem: minimum-average-makespan task assignment problem, which is suitable for scenarios where tasks are independent. To solve the problem, two greedy strategies of small-task-first-assignment and earliest-idle-user-receive-task are exploited. These two strategies always assign the shortest-sensing-time task to the user with the smallest expected processing time, which depends on the user's load (i.e., number of tasks already allocated to this user). The authors prove that these two strategies are near optimal. In [12], the authors also proposed another algorithm named Largest makespan sensitive Online Task Assignment (LOTA), which is for scenario where tasks are collaborative.

Prediction-based User Recruitment (PURE): The work in [13] focuses on the data uploading fees instead of worker incentives. In PURE, workers are divided into two classes. Workers in the first class are categorized as pay as you go (PAYG), who have to pay data uploading fees. Workers in the second class are categorized as pay monthly (PAYM), who are free to update data. There are many points of interest (PoIs) in the sensing area. Two workers are in contact with each other if they are in the same PoI. The mobility of workers is predictable according to their moving trajectories. If a PAYG meets a PAYM in a PoI, the PAYG can deliver their sensing data to the PAYM for uploading to reduce costs. The first problem in [13] is to select a PAYG user in the PoI as the best recruiter who has the highest probability of meeting a PAYM before a predefined deadline. To solve the problem, PURE computes the probability of a PAYG meeting any PAYM at any PoI before the deadline using a time homogeneous semi-Markov model. The PAYG with the highest probability in this PoI is chosen as the recruiter if there is no PAYM in this PoI. The second problem is to achieve a good tradeoff between the delivery ratio and the number of recruiters. In this scenario, a PAYG can employ another PAYG to deliver data to a PAYM. The authors proposed a delegation forwarding algorithm to tackle this issue. In this algorithm, an initial PAYG delivers sensing data to another PAYG if the probability of the new PAYG encountering a PAYM is higher than the current PAYG.

User Recruitment for Mobile Crowdsensing over Opportunistic Networks (MCN): This approach was proposed in [14]. In this scenario, sensing data need to be collected in a set of Points of Interest (PoIs) by some workers and uploaded when the workers encounter collection points such as WiFi APs. Workers can also exchange data if such exchanging leads to improved delivery performance. As illustrated in Fig. 2, the PoIs, workers, and collection points form various space-time paths (STPs). The goal is to select the minimal number of workers while guaranteeing there exists at least one space-time path from each PoI to a collection point. A greedy heuristic was proposed that selects workers on the STP minimizing the ratio of extra fees brought by new worker recruitments and the number of new PoIs covered by this STP in each iteration. The heuristic is proved to be near optimal. The authors also analyzed the scenario when worker mobility is uncertain but predictable. First, a time-space probability matrix is established for each worker. Second, a set of STPs and their formation probabilities are deduced. Third, the probability of each STP covering its related PoIs is calculated. Then the algorithm iteratively selects the STP leading to the minimal ratio of extra cost of new STP and the increase in PoI coverage until all PoIs are covered with probability one. The algorithm is also proved near optimal due to the submodular property of the utility function used.

iCrowd: The authors in [15] peopose a task assignment framework using piggyback crowdsensing such that sensing data are only uploaded along with 3G cellular phone calls, which is helpful for reducing the energy consumption of individual users. In iCrowd, the task region is divided into several sub-regions based on the distribution of cellular cell towers. The task period is divided into equal-length cycles. The main concern in iCrowd is the trade-off between *k*-depth coverage and incentives. A sensing sub-region is regarded as *k*-depth covered in a cycle if *k* sensing data from different workers are collected in the cycle. However, when the number of collected data exceeds *k*, the data quality will not increase any more. There are two classes of incentives in iCrowd: base incentive, which is a fixed incentive paid to each recruited worker, and bonus incentive, which is paid to workers for their involvement in each cycle. iCrowd aims to achieve the following two objectives:

- Maximize *k*-depth coverage under an incentive constraint.
- Minimize the total incentives under a *k*-depth coverage constraint.

To solve these problems, the authors first computed the probability of each worker placing at least one call in each cycle at each cell tower. The authors then proposed an iterative greedy algorithm that always chooses the best worker-cycle combination in each iteration, which maximizes a utility function defined as *k*-depth coverage improvement divided by incentive increment after adding a worker-cycle combination. The algorithm keeps running until the given incentive budget or coverage quality constraint is reached. This algorithm is proved to have an approximation bound.

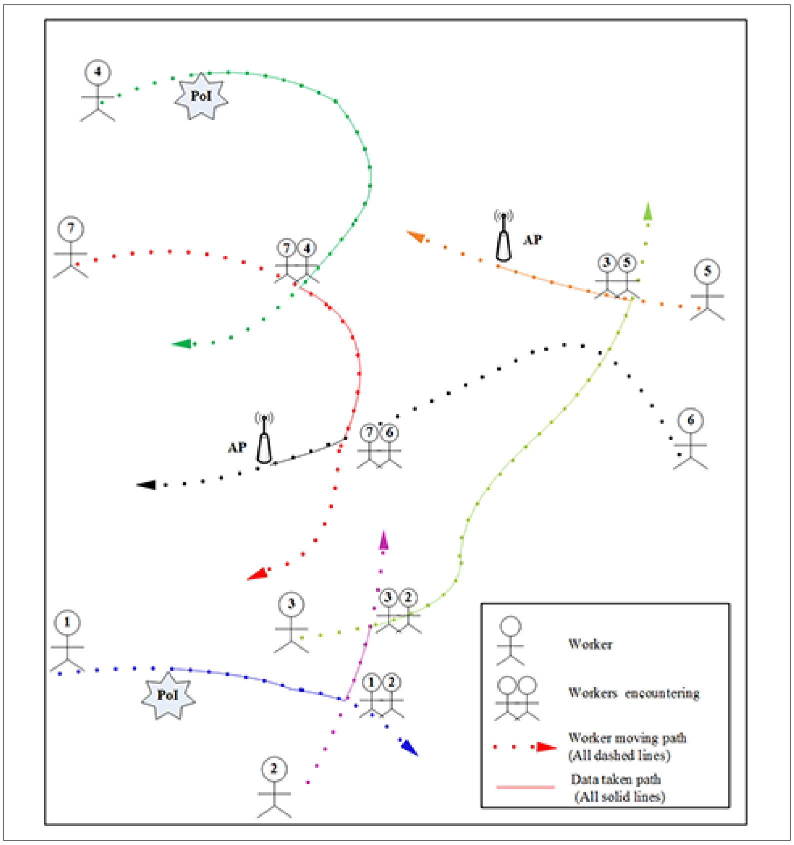

FIGURE 2. Illustration of worker recruitment for multi-hop data forwarding in opportunistic networks in [14].

EMC^3: The approach in [2] is an efficient data transfer solution for mobile crowdsensing. Like iCrowd, it also adopts piggyback crowdsensing along with 3G phone calls, which divides the task region into sub-regions based on the coverage of cell towers and also splits the task period into cycles. In each cycle, when a worker places a call, a central server should immediately decide whether or not to assign a task to this worker according to their call/mobility history and the probability that this worker would return the sensing results to this server piggybacked over another phone call in the same cycle. The assignment objective is to minimize the number of workers who have been assigned sensing tasks under the constraints of the expected amount of returned sensing results by different workers in each cycle, and full coverage of all cell towers. The authors break down this problem into three parts. First, when a worker places a call, the server determines if the worker is an eligible candidate that has a high probability of placing another call in this cycle based on their most recent call/mobility history. Second, the server estimates if the workers who have accepted the task still have sufficiently high probability to return the expected data. Third, if needed, the server determines if the task assignment should be sent to the current call-

Mechanisms	Participatory or opportunistic	oNline or oFfline	PoIs or full area	Task performed once or multi-times	Task completion cost	Metrics used for characterizing task quality	Heuristic or approximate solution
RSC [1]	O	Both	P	O	Per-worker recruitment costs	Task spatiotemporal coverage	H
EMC^3 [2]	O	N	F	M	Per-worker recruitment costs	/	H
QAI [4]	O	F	P	M	Per-worker recruitment costs	Data collection times	A
LRBA [6]	P	F	P	M	Worker travel costs and per-data collection costs	Data collection times	A
MCMF [7]	P	F	P	M	Worker travel costs	Data collection times	H
QAOTA [8]	P	N	P	M	Worker travel costs	Data collection times	A
QPA/TDA [9]	P	N	P	M	Worker travel costs	Data collection times	H
HGA [10]	P	F	P	O	Time penalty costs	Task duration	H
DPS [11]	O	F	F	M	Per-worker recruitment costs	Task spatiotemporal coverage	H
AOTA [12]	O	N	/	O	/	Minimum average task makespan	A
PURE [13]	O	F	P	O	Data transferring costs	/	H
MCN [14]	O	F	P	O	Per-worker recruitment costs	/	A
iCrowd [15]	O	F	F	M	Per-worker recruitment costs and per-data collection costs	Task spatiotemporal coverage	A

TABLE 1. Comparison of existing task assignment mechanisms based on different design criteria.

er. In this way, the required number of sensing data and full cell tower coverage are expected to be reached with high probability.

In this section, we surveyed 13 different task assignment mechanisms for mobile crowdsensing. Table 1 summarizes and compares these mechanisms based on different criteria.

Conclusion and Future Directions

In this article, we presented a comprehensive survey on typical task assignment mechanisms for mobile crowdsensing. Many task assignment mechanisms have been designed for different scenarios to achieve improved task quality or reduced task cost. However, research topics in this field are far from exhausted. Next, we list some potential issues in this field.

Joint Design of Opportunistic Sensing and Participatory Sensing

Existing work has focused on either opportunistic sensing or participatory sensing individually. However, such an approach to task assignment may either lead to unsatisfactory task quality (for the former) or high cost (for the latter). The joint design of efficient task assignment mechanisms using both opportunistic sensing and participatory sensing is a promising direction to achieve improved task quality at reduced cost. In this case, opportunistic sensing is expected to be maximally used for performing tasks whenever possible, while participatory sensing is used for performing those tasks that opportunistic sensing is unable to finish. In such joint mechanism designs, the following factors need to be considered: the moving behavior of workers and their distribution, task priority and distribution, and how to build a utility function to balance the choices between the use of opportunistic sensing and participatory sensing, and and so on.

Incentive Mechanisms for Task Assignment

Sophisticated incentive mechanisms can be employed to reward workers if they can provide more valuable results, or similar results but at lower payments/costs, or sensing results in locations with fewer workers visit. For example, workers who collect sensing data that are closer to ground truth can be paid with higher rewards since they contribute more important data to make the aggregate sensing results approach the ground truth. Also, the tasks in the region where fewer workers move around can be rewarded with higher incentives to encourage workers moving in that region to become involved. For designing efficient incentive mechanisms, the following factors need to be considered: the QoI requirement of tasks, bargain/cost requirements of different workers, worker distribution and their moving behavior, and so on.

Task Assignment Based on Spatiotemporal Correlation of Sensing Data

In many crowdsensing applications, sensing data exhibit high correlation characteristics spatially and temporally. Exploiting such spatiotemporal correlation properties by inferring the data in adjacent regions and time periods can greatly reduce data collection times and thus reduce the task cost with slight or little sacrifice in task quality. For this purpose, one problem is what kind of granularity the region and time period should be divided to best exploit the spatiotemporal data correlation property. Another problem is how to select the proper spatiotemporal blocks to collect sensing data and how to infer sensing data in spatiotemporal blocks where no or few data are physically collected. In this aspect, the authors in [16] combine compressive sensing, Bayesian inference, and active learning techniques to select a minimum number of sub-regions in each sensing cycle while reducing the missing data of unallocated sub-regions under a probabilistic data accuracy guarantee.

Task Assignment with Privacy Protection

Privacy concerns are also a critical issue in task assignment for mobile crowdsensing since the enthusiasm of workers might fade away if their privacy is at stake. In this aspect, privacy concerns typically contain identity and location disclosure. Regarding identity privacy protection, pseudonymity and *k*-anonymization are often used when making decisions on task assignment. Pseudonymity-based methods replace workers' identity information with a pseudonym; *k*-anonymization based methods make a worker's identity information indistinguishable from other $k - 1$ workers. Regarding location privacy protection, spatial cloaking and differential geo-obfuscation are often employed to tackle this problem, which obfuscate workers' real locations with cloaked locations. For example, the authors in [17] propose a two-stage task assignment optimization approach that utilizes spatial cloaking to obfuscate workers' locations while achieving high sensing coverage quality.

In summary, task assignment is a crucial issue in the design of mobile crowdsensing systems. Much work still needs to be carried out in this area to achieve a good tradeoff between task quality and task cost.

> In many crowdsensing applications, sensing data exhibit high correlation characteristics spatially and temporally. Exploiting such spatiotemporal correlation properties by inferring the data in adjacent regions and time periods can greatly reduce data collection times and thus reduce the task cost with slight or little sacrifice in task quality.

Acknowledgments

This work was supported in part by the National Natural Science Foundation of China (Grant numbers 61471339, 61531006, and 61173158). C. Li's work was supported partially by the Natural Sciences & Engineering Research Council of Canada and the RDC SensorTECH Program (Grant number: 5404-2061-101).

References

[1] H. To *et al.*, "Real-Time Task Assignment in Hyperlocal Spatial Crowdsourcing under Budget Constraints," *Proc. IEEE PerCom 2016*, Mar. 2016, pp. 1–8.

[2] H. Xiong *et al.*, "EMC3: Energy-Efficient Data Transfer in Mobile Crowdsensing under Full Coverage Constraint," *IEEE Trans. Mobile Computing*, vol. 14, no. 7, July 2015, pp. 1355–68.

[3] H. Zhang, J. Liu, and N. Kato, "Threshold Tuning-Based Wearable Sensor Fault Detection for Reliable Medical Monitoring Using Bayesian Network Model," *IEEE Systems J.* (in press, DOI 10.1109/JSYST.2016.2600582).

[4] M. Zhang *et al.*, "Quality-Aware Sensing Coverage in Budget-Constrained Mobile Crowdsensing Networks," *IEEE Trans. Vehic. Tech.*, vol. 65, no. 9, Sept. 2016, pp. 7698–7707.

[5] T. G. Rodrigues *et al.*, "Hybrid Method for Minimizing Service Delay in Edge Cloud Computing through VM Migration and Transmission Power Control," *IEEE Trans. Computers*, vol. 66, no. 5, May 2017, pp. 810–19.

[6] S. He *et al.*, "Toward Optimal Allocation of Location Dependent Tasks in Crowdsensing," *Proc. IEEE INFOCOM 2014*, Apr. 2014, pp. 745–53.

[7] Y. Liu *et al.*, "Taskme: Multi-Task Allocation in Mobile Crowd Sensing," *Proc. ACM UbiComp 2016*, Sept. 2016, pp. 403–14.

[8] Y. Kang *et al.*, "Quality-Aware Online Task Assignment in Mobile Crowdsourcing," *Proc. IEEE MASS 2015*, Oct. 2015, pp. 127–35.

[9] W. Gong, B. Zhang, and C. Li, "Location-Based Online Task Scheduling in Mobile Crowdsensing," *Proc. IEEE GLOBECOM 2017*, Dec. 2017.

[10] F. Yang *et al.*, "Heterogeneous Task Allocation in Participatory Sensing," *Proc. IEEE GLOBECOM 2015*, Dec. 2015, pp. 1–6.

[11] Z. Song *et al.*, "QoI-Aware Multitask-Oriented Dynamic Participant Selection with Budget Constraints," *IEEE Trans. Vehic. Tech.*, vol. 63, no. 9, Nov. 2014, pp. 4618–32.

[12] M. Xiao *et al.*, "Online Task Assignment for Crowdsensing in Predictable Mobile Social Networks," *IEEE Trans. Mobile Computing*, vol. 16, no. 8, Aug. 2017, pp. 2306–20.

[13] E. Wang *et al.*, "An Efficient Prediction-Based User Recruitment for Mobile Crowdsensing," *IEEE Trans. Mobile Computing* (in press, DOI 10.1109/TMC.2017.2702613).

[14] M. Karaliopoulos, O. Telelis, and I. Koutsopoulos, "User Recruitment for Mobile Crowdsensing over Opportunistic Networks," *Proc. IEEE INFOCOM 2015*, Apr. 2015, pp. 2254–62.

[15] H. Xiong *et al.*, "iCrowd: Near-Optimal Task Allocation for Piggyback Crowdsensing," *IEEE Trans. Mobile Computing*, vol. 15, no. 8, Aug. 2016, pp. 2010–22.

[16] L. Wang *et al.*, "CCS-TA: Quality-Guaranteed Online Task Allocation in Compressive Crowdsensing, " *Proc. ACM UbiComp 2015*, Sept. 2015, pp. 683–94.

[17] L. Pournajaf *et al.*, "Spatial Task Assignment for Crowd Sensing with Cloaked Locations," *Proc. IEEE MDM 2014*, July 2014, pp. 73–82.

Biographies

Wei Gong (gongwei11@mails.ucas.ac.cn) received the B.S. degree in computer science in 2011 from Zhejiang University, Hangzhou, China. He is currently working toward the Ph.D. degree in computer science at the University of Chinese Academy of Sciences. His research interests include mobile crowdsensing and mobile opportunistic networks.

Baoxian Zhang [SM'12] (bxzhang@ucas.ac.cn) received his Ph.D. degree in electrical engineering from Northern Jiaotong University (now Beijing Jiaotong University), China, in 2000. He is currently a full professor with the Research Center of Ubiquitous Sensor Networks at the University of Chinese Academy of Sciences (UCAS), Beijing, China. Prior to joining UCAS, he was a research scientist with the School of Information Technology and Engineering, University of Ottawa, Canada from 2002 to 2005. From 2001 to 2002, he was a postdoctoral fellow with the Department of Electrical and Computer Engineering, Queen's University, Kingston, Canada. He is currently an associate editor of *IEEE Systems Journal* and has served as a guest editor of several special issues, including for *IEEE Journal on Selected Areas in Communications* and *Elsevier Ad Hoc Networks Journal*. He has published over 150 refereed technical papers in archival journals and conference proceedings. His research interests cover network protocol and algorithm design, wireless ad hoc and sensor networks, Internet of Things, and IP networks.

Cheng Li [M'02, SM'08] (licheng@mun.ca) received the B. Eng. and M. Eng. degrees from Harbin Institute of Technology, Harbin, P. R. China, in 1992 and 1995, respectively, and the Ph.D. degree in electrical and computer engineering from Memorial University, St. John's, Canada, in 2004. He is currently a full professor on the Faculty of Engineering and Applied Science at Memorial University, St. John's, Canada. His research interests include mobile ad hoc and wireless sensor networks, wireless communications and mobile computing, switching and routing, and broadband communication networks. He is an editorial board member of the *Journal of Networks* and *China Communications*, and an associate editor of *Wiley Security and Communication Networks*. He has served as a co-chair for various technical symposia of many international conferences, including IEEE GLOBECOM and IEEE ICC. He has served as a TPC member for many international conferences. He is a registered Professional Engineer (P. Eng.) in Canada and is a member of the IEEE Communication Society, Computer Society, Vehicular Technology Society, and Ocean Engineering Society.