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A Survey of Task Allocation: Contrastive Perspectives From Wireless Sensor Networks and Mobile Crowdsensing

WENZHONG GUO[1,2,3], (Member, IEEE), WEIPING ZHU[1], ZHIYONG YU[1,2,3], (Member, IEEE), JIANGTAO WANG[4], AND BIN GUO[5], (Member, IEEE)

[1]College of Mathematics and Computer Science, Fuzhou University, Fuzhou 350116, China
[2]Key Laboratory of Spatial Data Mining and Information Sharing, Ministry of Education, Fuzhou 350003, China
[3]Fujian Provincial Key Laboratory of Networking Computing and Intelligent Information Processing, Fuzhou 350116, China
[4]School of Electronics and Computer Science, Peking University, Beijing 100871, China
[5]School of Computer Science, Northwestern Polytechnical University, Xi'an 710129, China

Corresponding author: Zhiyong Yu (yuzhiyong@fzu.edu.cn)

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ABSTRACT Wireless sensor networks (WSNs) and mobile crowdsensing (MCS) are two important paradigms in urban dynamic sensing. In both sensing paradigms, task allocation is a significant problem, which may affect the completion quality of sensing tasks. In this paper, we give a survey of task allocation in WSNs and MCS from the contrastive perspectives in terms of data quality and sensing cost, which help to better understand related objectives and strategies. We first analyze the different characteristics of two sensing paradigms, which may lead to difference in task allocation issues or strategies. Then, we present some common issues in task allocation with objectives in data quality and sensing cost. Furthermore, we provide reviews of unique task allocation issues in MCS according to its new characteristics. Finally, we identify some potential opportunities for the future research.

INDEX TERMS Mobile crowdsensing (MCS), task allocation, wireless sensor networks (WSNs).

I. INTRODUCTION

The rapid development of the city highlights the sensing needs for urban environment, target movements and human activities. Urban sensing tasks are characterized by large scape and heavy burden. Therefore, collecting sensing data effectively becomes focused issue. Wireless sensor networks (WSNs) and mobile crowdsensing (MCS) are two popular sensing paradigms and play important role in urban dynamic sensing.

WSNs are the specialized infrastructures that constituted by a large number of spatially distributed sensor nodes, which can communicate with each other through several hops of wireless link and collaboratively accomplish monitor tasks and collect corresponding data [1]. Due to the capacity of sensing, processing and communication, WSNs technology has found broad applications prospects, such as air quality monitoring [2], traffic control [3], [4], agricultural irrigation [5], etc.

In addition, with the development of wireless communication and sensor technology, some mobile devices (e.g., smart phone, iPads and wearable devices) have already equipped with various types of sensors (e.g., GPS, accelerometers, camera, gyroscopes, etc.) and show high capability in sensing and communication. A new sensing paradigm called MCS [6], in which mobile users leverages senors embedded in their mobile devices to collect and transmit sensing data, plays an important role in large-scale sensing and information sharing, and becomes a research issue in both academia and industry.

The realization of MCS mainly benefits from two concepts: crowdsouring [7] and mobile sensing. Concretely, large-scale sensing tasks that traditionally accomplished by specialized sensing infrastructures are outsourced to a group of ordinary mobile users. Compared to WSNs, MCS is a kind of grassroots sensing paradigm and has a number of advantages [8]: (1). MCS leverages mobile devices to sense or generate

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data instead of deploying specialized infrastructures, thus the sensing cost is quite low. (2). Different from static wireless sensor networks, or the sensor nodes move along a intended route, the inherent mobile users provide sufficient temporal-spatial coverage. Due to the advantages mentioned above, a broad range of MCS applications have been studied such as intelligent transportation [9], [10], environment monitoring [11], target identification [12], and so on.

Task allocation is a common concern both in WSNs and MCS. WSNs are composed by a set of sensing nodes with limited energy. Furthermore, it is infeasible to change or recharge to the battery because of the specific applications. So it is an important issue for WSNs to schedule nodes to accomplish sensing tasks and prolong the lifetime of whole network while guaranteeing the quality of information (QoI) in the target area. For MCS system, platform recruits mobile users to participate in sensing tasks and upload high quality data. From the perspective of mobile users, collecting and uploading sensing data devote their time and consume energy of mobile devices, even require them to change their original trajectory. Without any incentive to compensate for their effort, users may be unwilling to participate in sensing tasks. Besides, users vary in some specific knowledge and expertise, which causes diversity in data quality. From the perspective of platform, it expects to get high quality data, but reluctant to sacrifices much cost. Thus, to get high quality of sensing data under budget constraint, a advisable way is allocating the tasks to proper users, while accounting for the various initial locations of different users, sensing data reliability and sensing cost. Therefore, task allocation is an important issue both in WSNs and MCS.

Due to its importance, several studies have been conducted. These works discussed the task allocation problem in WSNs or MCS from different aspects, such as quality of sensing data, sensing cost, etc. For example, Wang *et al.* [13] analysed the unique features of MCS compared to general crowdsourcing and present an overview of task allocation from different type of problem formulation. However, few work summarized the common research problems both in WSNs and MCS, or some emerging problems in MCS. In fact, there are some similarities and differences in objectives and strategies for two types of sensing paradigm. Firstly, for some common issues (e.g., fault tolerant), the strategies of task allocation in WSNs are almost suitable in MCS. MCS applications can directly adopt these strategies. Secondly, some issues such as energy consumption, though the constraints in these two sensing paradigms may be different, the strategies in the MCS can learn from WSNs according to its new characteristics. Thirdly, some new issues (e.g., incentive mechanism, location privacy), which are not necessary discussed in WSNs, should be explored to meet the increasing requirements of MCS. To better understand the task allocation in these two sensing paradigms, a comprehensive overview of task allocation problem in both WSNs and MCS is desirable. In this paper, we focus on the comparison of task allocation problem in WSNs and MCS. We firstly analyze the common issues in these two sensing paradigms. Then, we present some distinct task allocation issues in MCS due to its new characteristics. In particular, the contribution of this paper can be concluded as follows:

- Analyzing the characteristics of WSNs and MCS, which indicates that the similarity and difference of task allocation problem in two sensing paradigms.
- Discussing some common issues of task allocation in two types of sensing paradigm, including data quality and sensing cost. We analyze the different strategies that adopt in two sensing paradigms, which can help researchers take good understanding of the problem of task allocation and corresponding methods.
- Reviewing some unique issues of task allocation in MCS that WSNs does not consider, such as incentive mechanism, travel distance of users and location privacy, which present distinct characteristics of task allocation in MCS.
- Investigating the some potential research directions in MCS task allocation, which may be more promising and meaningful in practical MCS applications.

Our main contribution can be concluded in Fig.1. The remainder of this paper is organized as follows: in Section 2, the characteristic of WSNs and MCS are analyzed. In Section 3, the common issues of task allocation in two types of sensing paradigm are discussed. Then, some distinct issues of task allocation in MCS are introduced in Section 4. Following that, we discuss research opportunities of task allocation in MCS in Section 5. Finally, conclusions drawn from this study are presented in Section 6.

II. CHARACTERISTICS OF TWO SENSING PARADIGMS

In this section, we briefly summarize the framework and present the characteristics of WSNs and MCS, which may lead to difference in objectives and constraints of task allocation problem.

The framework of WSNs is shown as Fig. 2, which consists of sensor nodes, sink nodes, Internet and task manage system. Typically, sensor nodes are embedded with a sensor unit, a processor, wireless communication module and power supply module, thus having processing, storage and communication capabilities. Sensor nodes not only collect and process the sensing data from their monitored area, but also store and manage the data transferred from other nodes. The sink nodes can be either a intensified sensor node, which equipped with enough energy to provide more memory resources and computing power, or a special gateway device only with wireless communication interface but no monitoring function. They usually has stronger processing, storage and communication capabilities. They mainly play the role in communicating between sensor nodes and wireless sensor networks, transmitting collected data information to external networks. Generally, sensor nodes collect and transmit the required information to the sink nodes by a hop or multi

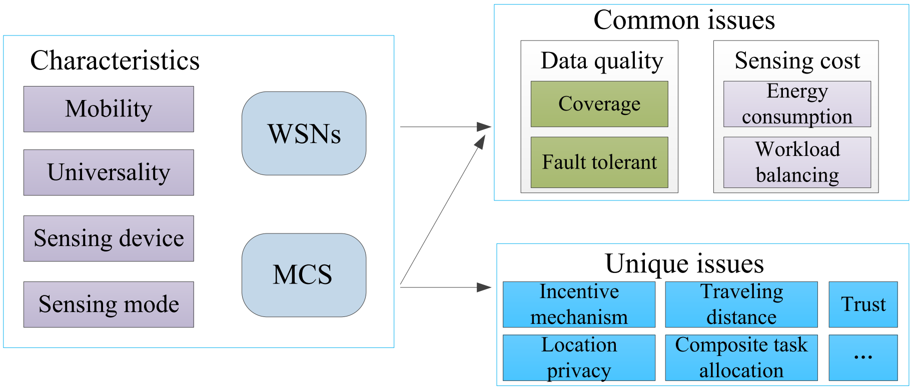

FIGURE 1. The main contribution of this work.

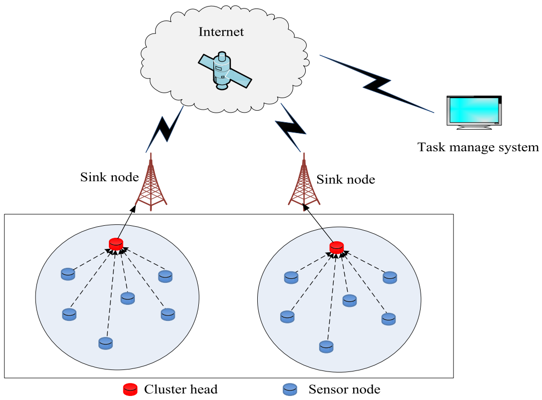

FIGURE 2. The framework of WSNs.

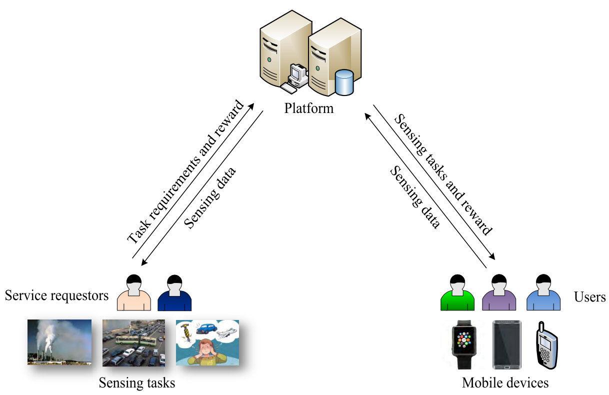

FIGURE 3. The framework of MCS.

hop wireless communication link. Then, the sink nodes send processed data to the task management system via satellite, Internet or mobile communication.

Different from WSNs, a MCS system consists of three components: service requestor, MCS platform and users. We show the framework of MCS in Fig. 3. The service requestors create sensing tasks and upload task requirements (e.g., the task context, the location and time, the number of users, etc.) to the MCS platform. MCS platform usually consists of a set of servers, which can store, analyze and integrate crowd data. After receiving the requirements from service requestors, MCS platform publishes the tasks and recruits well-suited users to perform tasks. Users leverage mobile devices sensing and upload the up-to-date local data to the MCS platform. MCS platform analyzes and aggregates the sensing data, then transmits to service requestor according to the requirements. To compensate for the users, MCS platform leverages incentive mechanism to pay some reward to users for their contribution.

According to the framework of WSNs and MCS, the participation of users is the chief difference between WSNs and MCS. The success of MCS benefits from the concept of "crowdsourcing", which is defined as outsouring a burdensome task to a large group of people [14]. In other words, a large-scale sensing task that traditionally completed by a specific infrastructure can be allocated to ordinary users who use their carry-on devices to collect sensing data. Mobile users collaborate consciously or unconsciously to complete the sensing tasks that is impossible completed by individuals alone. From the following perspectives, we analyze the differences of two sensing paradigms, which may cause different strategies or some unique issues in task allocation due to the new characteristics of MCS.

A. MOBILITY

Traditional WSNs deploy static or intended moving sensor nodes, which collect sensing data in a specific area and transmit the collected sensing data to their neighbor sink nodes by one hop or multi hops. Thus, coverage and communication distance of WSNs are limited. By contrast, the inherent mobility of users provides high spatiotemporal coverage compared to the WSNs [8]. According to whether users should change their regular routine to participate in sensing tasks, MCS can be classified into participatory sensing and opportunistic sensing. Participatory sensing indicates that users should change their routine to participate in sensing tasks. In this case, the travel distance is the main concern for users to determine whether participate in sensing tasks. In opportunistic sensing, users do not need to change their

TABLE 1. Characteristics of WSNs and MCS.

	Resource	Mobility	Coverage	Cost	Reusability	Data quality	Sensing mode
WSNs	limited	static or intentionally moved	low	high	low	high	physical space sensing
MCS	rich	moved	high	low	high	low	collaborative sensing of physical and cyber space

routine and participate in sensing tasks unconsciously. However, to recruit proper users, an efficient trajectory prediction is important in this case. Furthermore, sensing tasks are usually location-based. Collecting related data for these tasks may exposure the location of users. Thus, some new techniques should be adopt to protect users' privacy.

B. UNIVERSALITY

Traditional WSNs deploy application-specific infrastructures to collect sensing data. Consequently, it costs much money to deploy and maintain sensor nodes. To reduce the cost, a common practice is deploying much sensor nodes in the areas that are urgent need and few nodes in desolate areas. Thus, the collected data is not spatial-uniformly. Furthermore, sensor nodes consume battery energy during data collection and transmission. When the energy is exhausted, sensor nodes cannot be recharged or replaced due to the practical application [15]. Thus, it is difficult for WSNs to perform the large-scale sensing and data transmission tasks for long time.

MCS is a pervasive sensing paradigm. Instead of deploying application-specific infrastructures, MCS applications recruit original citizens to participate in sensing task. Even if some users may drop out collecting data during the required time, the platform will recruit new users to complete the task. With the development of city, MCS plays an important role in data collecting. However, some factors of users should be considered. Firstly, users may be unwilling to participate in sensing tasks due to the inherent selfishness. To motivate the mobile users' participation, incentive mechanisms should be considered in the process of task allocation. Secondly, with the development of MCS, sensing tasks become more and more complex and may require the users' expertise in some special field or carry the mobile devices embedded with required sensors to accomplish sensing tasks. Thus, the capability heterogeneity of users should be considered.

C. SENSING DEVICE

Sensor nodes in WSNs are elaborated to collect specific type of data (e.g., the air monitor only collect the air-quality data in a specific area). Due to the specificity, the quality of sensing data from WSNs is usually high. However, specific sensor nodes are hard to apply to collecting other type of data (e.g., traffic information video). Thus, the reusability of WSNs is low.

With the development of sensor technology, mobile devices such as mobile phone, wearable devices are embedded with various types of sensors, which can accomplish different types of tasks. The related departments do not need to deploy specific network infrastructures. However, different sensing devices vary in sensor type and performance, the collected data suffer from the issues of quality because of sensor performance. Due to the advantages of MCS, more and more applications leverage MCS to collect sensing data. From the perspective of individual user, how to cooperate sensors to maximize his benefit under limited sensing capability is also an important issue in MCS.

D. SENSING MODE

WSNs are physical sensing paradigm that composed of a set of sensor nodes with the ability of sensing, storage, and communication. These nodes cover the target area and collaboratively collect the sensing data. Once the system sets the sensing requirements of a task, WSNs can execute the sensing program according to the requirements without the involvement of users. For example, if the sensing cycle is set to one hour, the system will automatically collect the sensing data once a hour.

With the development of social network, platforms such as Twitter, Foursquare provide users' information. These information include location-based information and user content information [16]. Except for collect data from physical space, the information from social network play an important role in MCS to collect crowd sensing data. Because of the participation of users, the sensing data may integrate human intelligence and machine intelligence, which provides more intelligent information than WSNs. Take the task that sensing traffic information of a street as an example, except for the uploaded pictures, some comments from users can also provide important information to service requestor.

The summarization of the difference of characteristic between WSNs and MCS are shown in Table 1.

According to analysis above, in terms of task allocation, there are some difference in objects and constraints. On the one hand, there are some similar common issues that two paradigms concerned. However, due to the different constraints, the strategies may be different. On the other hand, with the participate of mobile users and other new characteristics of MCS, there are some new issues should be concerned in the task allocation. In the following two sections, we will present a systemic reviews of common issue of two sensing paradigms and new issues in MCS, respectively.

III. COMPARATIVE STUDY ON COMMON ISSUES

Data quality and sensing cost are two important concerns in task allocation. There are some common objects of task allocation in WSNs and MCS from these two perspectives.

However, Due to the differences in framework characteristics and application scenarios, the strategies adopted in the two sensing paradigms may be different. In this section, we present reviews of strategies that two sensing paradigms adopt to tackle the problem of data quality and sensing cost.

A. DATA QUALITY

Data quality is one of most important concern of two sensing paradigms in the process of task allocation. However, it difficult to give a common definition of data quality. Most researchers investigate the data quality problem from the two aspects: coverage and fault tolerant.

1) COVERAGE

Coverage is a key indicator for a sensing platform. It indicates how well the target areas can be observed. According to [17], the coverage can be described as monitor-quality of a network in the target area. The definition of coverage is closely related to applications but usually can be categorized into three types: point coverage, region coverage and barriers coverage [18]. Point coverage reflects the condition that a set of target points can be covered. In the region coverage, the objective is to cover a two-dimensional region. Barrier coverage indicates that sensor nodes detect a moving object which invade the deployment area [19]. Generally speaking, the definition of coverage in two sensing paradigms are not differ too much. However, there are some difference between strategies of getting high coverage.

a: COVERAGE IN WSNs

In the last few years, researchers are actively exploring the coverage problem in WSNs. In the process of sensor deployment, Yoon and Kim [20] studied the sensor deployment problem that aims to maximize the Boolean disk coverage under the giving type and number of sensor constraint. Then they devised a novel genetic algorithms to tackle this problem. Cao *et al.* [21] transferred the deployment problem to an multi objective problem, which simultaneously considered three objectives: extensive coverage, long network lifetime and high reliability. Then, they proposed a distributed parallel multi objective evolutionary algorithm to solve this problem.

After deployed, sensor nodes in the network collect and transmit the sensing data to the sink nodes. Since the energy of sensor node is limited, the performance of network may degrades with the time. In fact, the sensor nodes in WSNs share the same sensing task. It is not necessary to keep all node working during the whole lifetime. In addition, some applications like temperature monitoring may not require 100% coverage for whole target area. To reduce the energy consumption and prolong the lifetime of network, a practical strategy is selecting sensor nodes work alternatively, while meeting the coverage requirement. Danratchadakorn and Pornavalai [22] proposed a decentralized sleep scheduling protocol to maximize the coverage of network. In this protocol, every sensor create a neighbor table and cell value table, then exchange the coverage information with their neighbor sensor to decide which mode it should be on. Movassagh and Aghdasi [23] proposed a distribute method that exploiting game theory to select active sensor node to cover the target area. Sensor nodes compete to be active or inactive according to their coverage redundancy, activation cost, number of neighbors and uncovered regions. Similarly, Wang *et al.* [24] considered the coverage control in the underwater acoustic sensor networks (UASNs) and proposed a memetic algorithm to minimize the number of active nodes while guaranteeing coverage.

b: COVERAGE IN MCS

Different from WSNs, MCS does not need to deploy dedicated infrastructures. Alternatively, the platform in MCS directly selects suitable mobile users to meet the required spatial-temporal coverage. Typically, the platform divides the sensing duration into several cycles and specifies the target area into a set of subareas. It is assumed that if mobile users reach a subarea in a specific cycle, then he covers the subarea-cycle tuple. Due to the mobility of users, the application usually predicts the mobility of users before allocating the tasks. For example, Reddy *et al.* [25] considered the location, time constraints and transportation mode of users to model the mobility profile of users. Then, they proposed a coverage-based framework to select well-suited users to maximize spatial coverage. Zhang *et al.* [26] predicted the mobility of users using a Poisson model and then selected minimum number of users to meet the predefined temporal-spatial coverage. Xiong *et al.* [27] defined a temporal-spatial coverage called k-depth coverage, then they predicted the mobility of users and discussed task allocation problem with different incentive and coverage objectives/constraints in the Piggyback Crowdsensing (PCS) task model. Another work [28] defined a novel coverage metric called ''t-sweep k-coverage'', and proposed two methods to select smallest set of candidate users based on their check-in data to satisfy predefined coverage requirements. Zhang *et al.* [29] investigated coverage quality and proposed a approximation algorithm to select a subset of mobile users to maximize coverage quality under constrained budget. In [30], a greedy based multi tasks allocation framework for participatory sensing is proposed, which aims to maximize the overall coverage under shared budget. Wang *et al.* [31] firstly leveraged a strategy to discovery the mobility patterns of users from history trace and then devised different greedy-based task matching algorithm with the objectives of minimizing the cost and maximizing the coverage.

Besides, with the development of MCS, more and more applications leverage MCS framework to recruit mobile users. However, different tasks are heterogeneous in spatial-temporal requirements. For example, a spatial-temporal granularity of collecting noise data is different from collecting air quality, because noise changes more sharply with the time and space. Therefore, tasks allocation for heterogeneous tasks the should be considered. For example, Li *et al.* [32] estimated the probability of a participant to make a phone at target location and proposed a greedy-based participant selection algorithm for heterogeneous tasks to minimize the number of users while guaranteeing a certain level of coverage. Wang *et al.* [33] studied the heterogeneous multi tasks allocation problem, in which the involved tasks are different in spatial-temporal granularity but share the same participant resource. They constructed spatial-temporal correlation representation between multiple tasks and then proposed a decomposition and combination framework to tackle this problem. Song *et al.* [34] invested multi tasks allocation problem and proposed a metric called quality of information (QoI), which can be expressed as the ratio of the number of measurements of collected and needed for each task. The problem can be transformed to a knapsack problem and a greedy-based selection strategy is designed to solve the problem.

c: SUMMARY OF COVERAGE

According to analysis above, we conclude that there are two differences in coverage problem. Firstly, compared to the intended deploying sensor nodes in WSNs, MCS selects suitable users to participate in sensing tasks according to their trajectories. Probabilistic models are usually adopted in opportunity sensing to estimate the mobility of users. Thus, the coverage metrics in the MCS are usually probabilistic-based. Secondly, due to the coexist of multiple heterogenous tasks, the definition of coverage in MCS may be also heterogenous in term of spatial-temporal granularity.

2) FAULT TOLERANT

Fault tolerant is another important metric of quality of service of sensing network. It reflects the ability that the network works correctly even some unexpected circumstances occur. Thus, fault tolerant is also an important issue that should be considered.

a: FAULT TOLERANT IN WSNs

WSNs consist of a lot of sensor nodes that with limited energy. When the left energy blows a certain value, the sensor node may not work correctly. In addition, sensor nodes are usually deployed in hostile environment and easily be destroyed by malicious behavior of human, villainous weather, etc. Thus, fault tolerance mechanisms are necessary in task allocation to deal with serious consequences caused by sudden failure of nodes, and ensure the tasks successfully completed before the specified deadline.

The primary/backup (P/B) copy is the most popular technique for fault-tolerant in WSNs. It allows copy of tasks run on different sensor nodes. There are two modes of copy for a task, which named primary copy and backup copy. According to the execution time of backup copy, The primary/backup technique can be classified into three modes: active backup copy mode, passive backup copy mode and overlapping backup copy mode.

In the active backup copy mode, primary and backup copy are executed in different sensor nodes. The backup copy can execute normally even the primary copy failed to guarantee the correct results of the tasks. There is no requirement for the running time of these two copies of task, i.e., the two copies need not be synchronized. However, it will consume twice resource compare to the nonfault situation. Study in [35] considered the task allocation in industrial system where periodic and aperiodic tasks are coexist. Due to the unpredictability of aperiodic tasks, authors leveraged active backup copy mode to schedule primary and backup copies of aperiodic tasks by using the reserved processor time of periodic tasks.

Different from active backup copy mode, the passive backup copy mode runs the backup copy under the situation that primary copy fails. It does not run the backup copy if there is no fault in primary copy. But the disadvantage is that it encounter more time requirement. Pathan and Jonsson [36] proposed a fault tolerant global multiprocessor scheduling algorithm (FTGS), which leveraged the passive backup copy scheme to tolerate both task errors and processor failures that occur at any time even during the execution of recovery operation.

The overlapping backup copy mode combines the advantage of above modes. In this mode, primary and backup copy overlap in their running time and improve the performance of tasks. Guo *et al.* [37] proposed soft real-time task fault-tolerant allocation algorithm, which based on particle swarm optimization (PSO) in WSNs to minimize tasks execution time, save node energy cost, and balance network load. The proposed algorithm employs P/B technology and backup copy overlapping technology to achieve fault-tolerant mechanism. Zhu *et al.* [38] considered the quality of service and heterogeneous features of clusters, then proposed a fault-tolerant scheduling algorithm called QAFT, which employed the backup-copy overlapping technology striving to advance the start time of primary copies and delay the start time of backup copies under the time constraints.

b: FAULT TOLERANT IN MCS

For MCS, fault tolerant is also necessary. Users leverage the mobile devices to sense and upload sensing data, there are some circumstances that may affect the completion quality of sensing tasks. Firstly, similar to the sensing nodes in WSNs, mobile sensors may be blocked. Secondly, due to the heterogeneity of sensing devices, the quality of sensing data from different users vary greatly. Thirdly, users may exhibit some malicious behaviors and contribute sensing incorrect data intensionally. Finally, users in MCS may leave the target area before they complete the tasks, causing the sensing data can not be successfully sensed or uploaded.

In response to the above situations, MCS applications usually adopt strategies similar to the active backup copy mode in WSNs. That is, recruiting multiple users at one time to complete one task. For example, studies in [27] and [39], authors defined a spatial-temporal coverage and discussed how to select multiple users to maximize the coverage quality under budget constraint. To guarantee the validity of sensing data, recently, some mechanisms are proposed to quantify the trustworthiness of sensing data. For example, Pouryazdan *et al.* [40] proposed a new metric called collaborative reputation score to quantify the trustworthiness of sensing data. This metric is based on statistical reputation and social reputation. It is a weighted sum of previous and current reputation. The experiment results showed that the new metric can get better performance compared to solely vote-based or anchor-assisted scheme.

c: SUMMARY OF FAULT TOLERANT

Fault tolerant mechanisms in two sensing paradigms are similar. That is, they allocate the tasks to multiple sensor nodes. WSNs allocate tasks to multiple sensor nodes in case of tasks are unable to be completed on time due to the sensor nodes break down. For MCS, it recruits multiply users to guarantee data quality in case of mobile device failure or low-quality sensing data uploaded by malicious users. Furthermore, some trustworthiness mechanisms are introduced to measure the trustworthiness of users.

B. SENSING COST

The sensing cost is another concern in task allocation. An effective way to lower the cost is reducing the energy consumption and prolonging the lifetime of network. In addition, the workload of sensor nodes should also be considered. Because a energy-exhausted sensor nodes may affect the completion of tasks. Thus, we discuss the sensing cost from the perspectives of energy consume and workload balancing.

1) ENERGY CONSUMPTION

Energy expenditure for a sensing node is inevitable. For example, Verizon consumers 8.9TWh energy, that's the 0.24% of the total energy consumption of the U.S. [41]. The energy consumption grows exponentially with related applications. With the escalations of wireless network and mobile devices, energy-efficient wireless network has attracted a significant amount of research effort these years. The key problem for this issue is to trade off the energy consumption and quality of information. From the task allocation of view, researchers focus on how to schedule sensing nodes to participate in data collecting with low energy expenditure.

a: ENERGY CONSUMPTION IN WSNs

Sensor nodes in the WSNs are usually battery-constrained. And it is impractical to recharge battery during the running state of network [42]. Thus, deploying large number of sensing nodes and keep all node works to collect related data is infeasible and energy-consuming. An alternative approach is scheduling a subset of sensors in the working mode while others keep sleep mode to save energy and prolong the lifetime of network [43]. Zhao and Gurusamy [44] proposed an approach to schedule the active sensors and maximize the lifetime of WSNs, which can maintain a full coverage of target areas and can be connected to sink nodes by direct links or by multi hops route traversing. If the full coverage or the predefined connectivity cannot be satisfied, Zhao assumed that the deployed WSNs reached its lifetime. Chen *et al.* [45] introduced Trap Cover Optimization (TCO) algorithm to achieve the goal that scheduling the activation sensor nodes while guarantee the uncovered hole is no greater than a given threshold. Lu *et al.* [46] attempted to prolong the lifetime of WSNs by switching on the sleep-mode sensor in target spots. Yu *et al.* [47] considered the energy consumption of sensing, computing communication and sleeping, they mapped the workload distribution problem into graph partition problem and formulate the energy consumption and the time constraint of the nodes in WSNs.

Node clustering is an another way to reduce the energy consume and prolong the life of network. Every cluster is managed by the cluster head (CH). CH play an important role in coordinating the nodes' activities. Nodes in the cluster transmit to the CH, then CH transmits the aggregated data to other CH or sink nodes, thus it can reduce the energy consumption [48]. Naranjo *et al.* [49] proposed a new technique, named *P-SEP*, which attempt to select CH to save energy and prolong the lifetime of network. *P-SEP* considers the number of sensor nodes that associate with CH and minimizes the distance between CH fog nodes. Simulations indicated that P-SEP prolong the lifetime of network compared to the baseline algorithm.

b: ENERGY CONSUMPTION IN MCS

Similarly, it is important for MCS system to minimize the energy consumption of mobile users' devices because high energy consumption reduce the users' participation willingness [50]. An energy-efficient task allocation scheme aims to select minimal number of users while ensuring a predefined data quality. Sherchan *et al.* [51] proposed a framework, Context-Aware Real-time Open Mobile Miner (CAROMM), to reduce the amount of data sent and energy usage in the process of data collection while providing comparable level of accuracy to traditional sensing model. Lane *et al.* [52] proposed PCS system, which collects mobile sensing data when mobile users place phone calls or use applications to lower the energy overhead of users. Zhang *et al.* [26] proposed a user recruiting framework, *CrowdRecruiter*, which aims to select minimal number of users while satisfying probability coverage constraint. Liu *et al.* [53] modeled an energy-aware recommended sampling behavior and computed the task rejection probability. Then, they formulated a constraint optimization problem and devised a suboptimal solution to tackle the problem. The study in [54] proposed an energy-efficient data collection framework, whose objective is to minimize the energy consumption while maximize the utility of collected data. Then, authors developed an Android application to measure the performance of proposed framework. Anjomshoa and Kantarci [55] proposed a scheme called SOBER-MCS to assign tasks to users, which considers sociability and mobile battery level.

Another way of reducing the energy consumption is to reduce the number of allocated tasks in view of spatial-temporal correlations. For example, sparse mobile crowdsensing [56], which selecting small portion of subareas for sensing and inferring data of remaining subareas according to spatial-temporal correlation among subareas, thus lowering the energy consumption and incentive. Based on this conception, CCS-TA [57] was proposed to monitor real-time temperature and air-quality in the city. It iteratively selects salient cell to collect sensing data until the predefined data quality are satisfied. Then, the missing data is deduced by combining with Bayesian inference and active learning mechanisms. Evaluation results on real-world datasets show the applicability of CCS-TA.

c: SUMMARY OF ENERGY CONSUMPTION

Though both two sensing paradigms consider the energy consumption, the strategies are different. WSNs alternately select subset of sensor nodes keeping in active state and the others in sleep state to maximize the performance and prolong the lifetime of network. Then, node clustering mechanism is introduced to reduce the consumption of communication energy. In MCS, researchers aim to minimize the number of task allocation. For example, recruiting minimal number of users, or selecting minimal number of subareas to collect sensing data.

2) WORKLOAD BALANCING

Except for minimizing energy consumption, the workload balancing should be considered. Because overload to some specific sensor nodes may lead to premature death and affect the performance of network. In this section, we will discuss the workload balancing strategies in two sensing paradigms.

a: WORKLOAD BALANCING IN WSNs

As we know, the CH consumes more energy than other sensor nodes in the cluster. That is, the workload is unbalance among sensor nodes. To solve this problem, a popular way is reclustering and rotating the CH among the sensor nodes. Neamatollahi *et al.* [58] proposed Round-Based Policy (RBP), which splits network operations into several rounds and group sensors into clusters at the beginning of every round to extend the lifetime of network. However, RBP also consumes much energy because of the unnecessary reclusterings. Authors further proposed a Dynamic Hyper Round Policy (DHRP) to mitigate this situation by clustering only in the dynamic hyper round. DHRP is applicable to data collection and outperforms than well-known clustering protocol. In [59], a hierarchical clustering-task scheduling method is proposed, which including local clustering and global clustering. During the local clustering, only a part of nodes execute the clustering process in each super round for the load balancing goal. Global clustering is performed at the end of every end of global hyper round to refresh the entire network structure.

b: WORKLOAD BALANCING IN MCS

With the development of MCS, more and more applications leverage the MCS platform to recruit users. These applications compete with each other in a limited user resource [60]. For individual user, due to the limit battery and other computing resource, the maximum number of tasks that each user can completed is limited. To avoid overloading to individual user, a common way is assuming a maximum workload for each user. Recently, several works considered this situation and proposed the multi tasks allocation frameworks in MCS. In [60], a novel multi tasks allocation framework named *PSAllocator*, which considers the maximum workload of each user, was proposed. *PSAllocator* defined a system utility which considers the spatial-temporal coverage. To get optimal system utility, *PSAllocator* predicts the possibility of users to connect to cell towers according to their historical mobility data. Then, an iterative greedy algorithm is proposed to optimize the task allocation. In our previous work [61], we investigated a multi tasks allocation problem that considers the heterogeneity of users (including the type of sensors and the maximum workload of users). A greedy discrete particle swarm optimization with genetic algorithm operation is proposed to maximize the number of completed tasks.

c: SUMMARY OF WORKLOAD BALANCING

Both WSNs and MCS consider the workload balance. WSNs adopt the active-sleep scheduling and the cluster head rotation to prevent sensor nodes premature death and affecting the data collecting in target area. However, MCS considers the resource limitation of individual by and assuming a maximum workload to every user. Since heavy burden will hurt the enthusiasm of users to collect sensing data.

Table 2 lists the subset of related works about common issues of task allocation in two sensing paradigms. We hope that it can help readers quickly retrieve the related papers and understand the related strategies.

IV. UNIQUE ISSUES FOR MCS

The involvement of mobile users in the MCS is the chief characteristic compared to traditional WSNs. So some important factors caused by mobile users should be considered in the process of task allocation in MCS. These factors lead to some new directions in MCS, In this section, we will talk about some unique issues in the MCS.

A. INCENTIVE MECHANISMS

Incentive is important to motivate the users to participate in MCS applications. Firstly, when users participate sensing tasks, it is inevitable to consume resource of users' devices, including computation, communication, and energy [62]. Particularly, for some special applications, mobile users should change their intended routine and move to the specific location to complete sensing task. In addition, participating in sensing task may expose location of users. Without an effective incentive mechanism, users may not willing to keep active to participate in sensing tasks sharing their data. Generally, the incentive mechanisms can be categorized into monetary incentive and nonmonetary incentive from the perspective of incentive type.

TABLE 2. A summary of common issues of WSNs and MCS and task allocation strategies.

issue	paradigm	strategy	reference
coverage	WSNs	active-sleep schedule	[22]
	WSNs	game theory	[23]
	WSNs	memetic algorithm	[24]
	MCS	greedy select multiple users	[26]
	MCS	greedy select multiple users	[27]
	MCS	greedy select multiple users	[28]
fault tolerance	WSNs	active P/B technology	[35]
	WSNs	passive P/B technology	[36]
	WSNs	overlapping P/B technology	[37]
	MCS	greedy select multiple users	[27]
	MCS	greedy select multiple users	[39]
	MCS	trustworthiness assessment	[40]
energy consumption	WSNs	active-sleep schedule	[43]
	WSNs	active-sleep schedule	[46]
	WSNs	node clustering	[49]
	MCS	select minimal number of users	[26]
	MCS	select minimal number of users	[50]
	MCS	compressive sensing	[56]
workload balancing	WSNs	re-clustering	[58]
	WSNs	re-clustering	[59]
	MCS	assume a maximum workload	[60]
	MCS	assume a maximum workload	[61]

1) MONETARY INCENTIVE

Monetary incentive encourages users by paying them rewards and usually shows a better incentive effect [63]. Auction mechanism is the most popular method in monetary incentive, which indicates that users bid for the sensing data, then platform selects subset of users with lowest bidding to contribute the sensing data.

Reverse auction incentive mechanism has attracted substantial attentions these years. In reverse auction, platform publishes the tasks. Users compete with each other to accomplish these tasks by lowering their bids until the bids keep unchanged. This mechanism selects the subset of users with minimal cost to maximize the profit of platform. To avoid the users who lost in the previous reverse auction dropping out, Lee and Hoh [64] proposed a novel Reverse Auction Dynamic Price with Virtual Participation Credit (RADP-VPC) incentive mechanism, which grants them a virtual credit and increases the chance that they can win in the next auction. Compared to Random Selection with Fixed Price (RSFP) incentive mechanism, RADP-VPC not only reduces the incentive cost but also improves the fairness of incentive distribution and social welfare. Jaimes *et al.* [65] combined the RADP-VPC with location of users, coverage and budget constraints, then proposed a greedy-based incentive algorithm (GIA). Simulation results show that the GIA increases the coverage with the similar budget compared to RADP-VPC. Zhao *et al.* [66] investigated the task allocation problem, whose objective is selecting subset of users to maximize the total value of service under a constraint budget. To motivate the mobile users' participation, they proposed two types of online incentive mechanism, called OMZ and OMG. In [67], a combinatorial reverse auction mechanism is proposed, in which users bid for the tasks according to their location and service coverage. Platform's incentive mechanism consists two components. The first one is the winning bids determining and the second one determines the critical payment to each winning bid. The study in [68] proposed a Lyapunov-based VCG auction policy, which consists of allocation rule, payment rule and updating rule. Allocation rule selects the winner who maximize the social welfare in each time slot. Payment rule pays one user biding according to the total cost of other users. Updating rule adjust the updating strategies according to the users' truthfulness. The results show that the proposed strategies not only reduce the users' dropping probability, but also increase the social welfare. Recently, a data-enhanced reverse auction incentive mechanism, TaskMe is proposed in [69]. In TaskMe, users upload their collecting data and bid to the platform. Platform dynamic selects the winner based the data quality and bid.

Stackelberg game is a game model with two roles called leader and followers. The leader firstly takes action and the followers can only adjust their actions according to the leader to maximize their utility. This game is used to design incentive mechanism due to the similar behavior. Duan *et al.* [70] used the Stackelberg game to model the interaction between platform and users. Specifically, the platform announces the total reward and the predefined number of users. Each user decides whether to participate in the task according to the total reward and number of users. When it reaches the state of Nash equilibrium (NE), the platform selects subset of users with lowest cost to maximize its profit. Similarly, in [71], a platform-centric incentive mechanism is proposed, in which platform plays the role of leader and announces its reward, each mobile user plays the role of follower and strategies its sensing time to maximize the utility.

2) NONMONETARY INCENTIVES

The popular nonmonetary incentive includes gaming incentive, social relation incentive and virtual credit incentive. Gaming incentive incorporates game element into crowdsensing and stimulates users to participate in sensing tasks. For example, the study in [72] introduced a gaming incentive to motivate users to participate in location-based services. The incentive mechanism determines the game points and coupon points according to the quality of service, which computed by online machine learning. Then users determine whether participate in collecting data.

Social relation incentive refers to make use of relationship in social network and motivate users participate in sensing tasks. Considering the intrinsic selfish of users, Bigwood and Henderson [73] used preexisting social network information to detect and discourage the selfish users.

In virtual credit incentive mechanism, users get virtual credit, which can be directly or indirectly transferred into real currency, as reward after participate in sensing tasks. Chou *et al.* [74] and Lan *et al.* [75] introduced a incentive mechanism based virtual credit to motivate users to contribute their bandwidth and data. The amount of credit that users earn depends on their unity of data. For example, a participate who upload a high resolution video clip earn more credits than who upload low resolution video clip.

B. TRAVEL DISTANCE

For some special crowd sensing applications, platform requires users to move from their current location to the location of task. For example, taking photos for a building, collecting traffic dynamics information for a specific street, etc. In this case, the moving distance become primary concern for users. Generally speaking, the reward is proportional to moving distance. So researchers try to minimize the moving distance of users and reduce the sensing cost. Guo *et al.* [76] investigated the participant selection problem for time-sensitive tasks. Due to the emergency of tasks, platform should select users who are nearest to the location of tasks. To address this problem, authors proposed greedy-enhanced genetic algorithms, which firstly designed a greedy algorithm to select task-worker tuple with least distance and assign the task to corresponding worker. Then genetic algorithm is elaborately designed to further improve the results of greedy algorithm. In [77], to minimize the total distance of users, authors divided the spatial task assignment problem in two stages. In the first stage, platform solves the task assignment problem using cloaked locations. In the second stage, users individually fine-tuned their assignments using their own exact locations. The proposed greedy algorithms at each stage show the efficient and robustness. Liu *et al.* [78] considered the FPMT (few users, more tasks) problem, and used Minimum Cost Maximum Flow (MCMF) theory to maximize the completed tasks and minimize the total distance of users. Liu *et al.* [79] studied task allocation in food delivery network, which select minimum number of taxis and travel distance to reduce the cost. Then, they designed two-stage algorithm to solve the problem.

C. TRUST

As a open data-collecting paradigm, there may be some unreliable users who are intend to provide a wrong sensing data [80]. Assessing and guaranteeing the data quality is a nontrivial work in MCS [81]. Furthermore, trust mechanism is an important measure of data quality and has been considered by researchers. For example, [82] proposed a reputation-based scheme, called Trustworthy Sensing for Crowd Management (TSCM) to assign task to mobile devices. Amintoosi and Kanhere [83] proposed a application-agnostic reputation framework for social participatory sensing systems, which assess the both quality of contribution and the trustworthiness level of users, then assigned a reputation score to user using PageRank algorithm. Pouryazdan *et al.* [84] adopted vote-based trustworthiness with trusted entities to assess trustworthiness of a smartphone user. The trusted entities called trustworthy anchor, who have 100% reputation and with the capable of voting for trustworthiness of other users. Zhao *et al.* [85] defined a user reputation model, which considered the history reputation and users' contribution for current task. Then, a reputation-based user selection method is proposed to guarantee the data quality. Because of the limited budget, the platform can only select the users with higher reputation.

D. LOCATION PRIVACY

Different from WSNs, in which sensor nodes are deployed in target areas and it is nothing to expose the location of nodes. In MCS, however, the platform should know the location of mobile users so that the tasks can assigned to proper users, who are near to the location of tasks. This indicates that users risk their location privacy when they participate in sensing tasks, which reduces the users' participation [86]. Though the selected users can be compensated with incentive, the remaining users may get discouraged because their location privacy sacrificed in vain. Therefore, location privacy should be carefully considered during the process of task allocation.

The popular location privacy-preserving mechanisms include cloaking [87] and dummy points [88]. However, their common drawback is that expected privacy will be impaired if the adversary has prior knowledge about users and location [89]. To address this problem, differential privacy has been introduced to protect location. It works by mapping one actual location to another according to a predefined probability matrix P, in which the probability of any two actual location map to the same obfuscate location is similar. Typically, more similar the probability is, more harder for adversary to distinguish the actual location. Wang *et al.* [90] proposed a location-preserving task allocation framework which uses differential geo-obfuscation to protect users' location during the process of task allocation.

E. COMPOSITE TASK ALLOCATION

Typically, WSNs deploy specific sensor nodes to collect one type of sensing data. However, there are some complex tasks in real-world scenarios, which consist of several subtasks and each subtask requires different types of sensor to sense data. The final sensing data aggregated from these subtasks. Such complex task can be called composite tasks [13]. For example, air quality monitoring task is an composite task and require multiple types of sensor (e.g., CO_2 sensor, CO sensor). To complete composite tasks, plenty of different types of sensor nodes should be deployed in WSNs and one type of senor nodes can only collect one type. Fortunately, a mobile device of MCS can afford multiple and various types of sensors embedded in it.

However, the users may not preassemble the required sensor, or the remaining battery power cannot support for the whole composite task, causing the task allocation for composite tasks more complicated. There are two challenges in task allocation for composite tasks. Firstly, the solution space grows exponentially because the granularity elaborates to the subtask rather than the whole composite task. Secondly, the optimal allocation of composite tasks should also take some complex factors into consideration, such as the trade off between the overall quality and total cost, users' sensing capacity for different subtasks, the heterogeneous spatiotemporal granularity of each subtask, etc. There are already some works in composite task allocation. For example, Cheng *et al.* [91] investigated the assignment for multi skills oriented spatial tasks, the objective is to map the required skills of tasks to skills of users and maximize the users' benefit under the budget constraint.

Furthermore, tasks are usually belong to different domains. Traditional WSNs is elaborated to collect high quality data for special domain. As for MCS, users have different qualities on different domains. To get high quality of sensing data, it is important to select users who with the skills that tasks involved. Zheng *et al.* [92] leveraged domain knowledge to model the users' quality and designed a online task assignment algorithm to assign k tasks with the highest benefit to the users. In [93], a framework for task assignment in knowledge-intensive crowdsouring is proposed, which considered the users' expertise, wage requirements, and availability. Reference [94] modeled the tasks and users using a skill taxonomy tree, which allowing to reason about skill substitutions and assign the task to suitable users in participatory crowdsouring. Song *et al.* [95] proposed a specialty-aware task allocation problem, in which tasks are complex and require users complete tasks collaboratively. They designed two heuristics algorithms to maximize the completed tasks according to tasks' budget and users' skills.

V. FUTURE RESEARCH OPPORTUNITIES

Although task allocation in the MCS has made great success. There are still some limitation in current research. In this section, we highlight some picture novel and exciting opportunities for the future research.

A. HYBRID DESIGN OF WSNS AND MCS

Existing work about task allocation is solely based on either WSNs or MCS framework, and the interlinking of these two forms of paradigm has little been explored. WSNs can get high quality of sensing data but it costs much to deploy and maintain the network. MCS is a novel sensing paradigm but lose efficiency under the circumstance that there are few users available. Based nature of these two sensing paradigms, there may be a hybrid sensing paradigm, which integrates the WSNs and MCS and can better coordinates the data quality and the sensing cost. For example, a hybrid framework that collaborates the cyber-physical-social space are proposed in [16]. There are several advantages of hybrid sensing paradigm. From the spatial-temporal perspective, on one hand, there is more chance to recruit users in the flourishing region and easily to get higher quality sensing data. In some remote areas, the poor user resource hardly support the MCS to get adequate sensing data. The WSNs can compensate for this situation. On the other hand, users can accomplish most of sensing tasks during the daytime. Sensor nodes in the WSNs can keep a sleep mode to reduce energy consume. During the nighttime, there are few users available, hybrid sensing paradigm can schedule the sensor nodes in WSNs to collect related data. Thus, the hyper sensing system can get almost full spatial-temporal coverage. From the data quality perspective, the aggregated data from WSNs and MCS can provide more intelligent service. However, in the hybrid sensing framework, how to jointly schedule this two paradigm to guarantee the data quality is a higher level task allocation problem and remains a challenge issue.

B. LEARNING ASSISTED TASK ALLOCATION

Generally, users in MCS are heterogenous. Related assumptions for heterogeneous users are based on devices. For example, different users carry different type of devices and can complete different types of sensing task. Our previous work [61] considered the type of sensors in mobile devices. However, the human factor should be considered in practice. Users are differ in participate willing, participation habits, abilities and reputation. For participate willing, users may reject the assigned sensing tasks due to lack of time. For participation habits, users may prefer to complete sensing tasks without changing their intended routine or update sensing data without take mobile phone out of their packet. Also, the level of skills to satisfy the required ability are vary among users. These factors should be considered in process of task allocation. To get information of these factors, a straightforward way is provided by users when they apply for the sensing tasks. However, some malicious users may lie about their related information to get more reward from platform. Alternatively, we can learn these information from their historical data. For example, logistic-regression is used in [96] to learn users' attributes such as proximity to target area, payment and task context from historical data. Micholia *et al.* [97] identified social media users expertise according to their past media activities and encouraged them to perform some task under limited budget. Unfortunately, due to the reason of privacy, the historical data of users are not always available [98]. A promising way to tackle this situation is learn users' behavioral pattern from some similar tasks and get some valuable information before task assignment.

C. SPATIAL AND TEMPORAL CORRECTION

Existing MCS task allocation for multiple tasks assumed that tasks do not run independently but compete with each other for the shared participant resource. However, for some specific situations, tasks can share same sensing data or the sensing data of one task can be inferred from other task due to the spatial and temporal correction. For example, there are two sensing tasks that aim to collecting information of traffic flow in the closer areas at same sensing cycles, respectively. In this situation, platform just recruits users to collect one task, and inferred the related information of the others to reduce the number of users. To achieve this, two challenges should be considered. Firstly, the relationship between two task should be analyzed, including sensing context, spatial and temporal correction. Secondly, how to design an efficient task allocation scheme that not only collecting data for the target task, but also inferring the data of other related task with high accuracy.

D. CLUSTER-BASED TASK ALLOCATION

The existing task allocation operated with the ''platform-users'' model, in which platform allocates the task to the users and users upload the sensing data to the platform directly. There are some shortcomings for this model. Firstly, the data collecting lacks a supervision mechanism, users may upload a low quality data deliberately. Secondly, uploading sensing data from every user increases the communication energy consumption. Inspired the clustering mechanism in WSNs, a rational way is establishing a three level sensing model, i.e., ''platform-cluster-users''. Platform firstly groups users into cluster according to their location or other related factors, and selects a user as cluster head. Then, platform assigns the sensing tasks to cluster head. Cluster head further assigns the sensing tasks to the users in his cluster. Users transmit the sensing data to cluster head and cluster head uploads the aggregated data to platform. However, there may be some new shortcomings for this mechanism. For example, users and cluster head may collude with each other to upload low quality data together. Therefore, a effective mechanism to make cluster head and users supervise each other is urgent needed.

VI. CONCLUSION

Task allocation is an important issue both in WSNs and MCS. In this paper, we present a survey of task allocation problem in these two sensing paradigms from the contrastive perspective. Firstly, we analyze different characteristics of WSN and MCS, which may cause some different issues and strategies in task allocation. Then, we provide a review of common issues in terms of data quality and sensing cost in these two sensing paradigms. Further, we give a review of unique issues of task allocation in MCS because of the involvement of human. Finally, we outline some potential opportunities in the future research.

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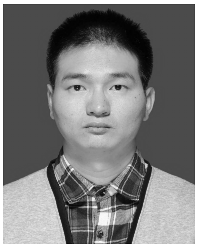
WENZHONG GUO received the Ph.D. degree from the Department of Physics and Information Engineering, Fuzhou University, Fuzhou, China, in 2010, where he is a Professor and the Director of the Fujian Provincial Key Laboratory of Network Computing and Intelligent Information Processing. He is also the Vice Director of the Key Laboratory of Spatial Data Mining and Information Sharing, Ministry of Education. He was a Postdoctoral Research Scholar with the Department of Computer Science, National University of Defense and Technology, Changsha, China, from 2011 to 2014, a Visiting Professor with the Faculty of Engineering, Information, and System, University of Tsukuba, Japan, in 2013, and a Visiting Professor with the Department of Computer Science and Engineering, State University of New York at Buffalo, USA, in 2016. His research interests include the fields of wireless sensor networks, network computing, and mobile crowdsensing.



WEIPING ZHU received the B.S. degree in information and computing science from Fujian Normal University, Fuzhou, China, in 2014 and the M.S. degree in computer applications technology from Fuzhou University, Fuzhou, in 2016, where he is currently pursuing the Ph.D. degree with the College of Mathematics and Computer Science. His research interests include pervasive computing and mobile crowdsensing.

ZHIYONG YU received the M.E. and Ph.D. degrees in computer science and technology from Northwestern Polytechnic University, Xi'an, China, in 2007 and 2011, respectively. He is an Associate Professor with the College of Mathematics and Computer Science, Fuzhou University, Fuzhou, China. He was also a Visiting Student with Kyoto University, Kyoto, Japan, from 2007 to 2009, and a Visiting Researcher with the Institut Telecom SudParis, France, from 2012 to 2013. His current research interests include pervasive computing, social computing, mobile social networks, and participatory sensing.

JIANGTAO WANG received the Ph.D. degree from Peking University, Beijing, China, in 2015, where he is currently an Assistant Professor with the Institute of Software, School of Electronics Engineering and Computer Science. His research interests include mobile crowdsensing, mobile computing, and ubiquitous computing.

BIN GUO received the Ph.D. degree in computer science from Keio University, Japan, in 2009. He was a Postdoctoral Researcher with Institut Telecom SudParis, France. He is a Professor with North-Western Polytechnical University, China. His research interests include ubiquitous computing, mobile crowdsensing, and human–computer interaction.