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Review Article

A Survey of Application and Key Techniques for Mobile Crowdsensing

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Mobile crowdsensing (MCS) uses ubiquitous smart devices and network access technology to migrate sensing tasks from a centralized platform to a distributed computing terminal across time and space and provides new approaches for solving large-scale, diversified, and complex sensing problems. MCS research is of great importance and has attracted wide attention from researchers. Accordingly, this article summarizes the current research status of MCS. First, the typical applications of MCS are summarized. Then, the research status of key technologies, such as task allocation, incentivizing, data transmission, quality assurance, and evaluation methods, is considered. Finally, future research directions of MCS are given to provide a reference for in-depth MCS research.

1. Introduction

In recent years, various handheld smart devices (e.g., smartphones and tablet computers) have been widely popularized and have become an indispensable part of daily life [1–3]. Furthermore, with the rapid development of sensor technology and embedded technology, these ubiquitous handheld smart devices have integrated various sensors, such as gravity sensors, speed sensors, and global positioning systems (GPSs), endowing these handheld smart devices with powerful computing and sensing capabilities [4–6].

Handheld smart devices rely on built-in sensing and storage functions, as well as powerful computing and communication capabilities, to create sensing units with abundant software and hardware resources [7]. These various built-in sensors can help their carriers sense the surrounding environment and obtain various real-time and accurate sensing data [8]. In addition, smart devices can use communication technology to enable people to quickly and dynamically share acquired sensing data [9]. These favorable characteristics have rapidly promoted the development of the emerging sensing paradigm of mobile crowdsensing (MCS) [10].

Compared with traditional wireless sensor networks, MCS not only achieves wider coverage at a lower deployment cost but also has the advantage of more flexible network maintenance [11]. Since the research of MCS has made great progress, to deeply understand the concept and development trend of MCS and promote research in this field, it is meaningful to summarize the research progress.

The remaining parts of this article are as follows: typical applications of MCS are introduced in the second part; then, in the third and fourth parts, the research status of key technologies, such as tasking allocation, incentive, data transmission, quality assurance, and evaluation methods, is summarized. Finally, future research directions of MCS are presented.

2. Basic Theory and Application of MCS

In this part, we introduce the basic theory and typical applications of MCS.

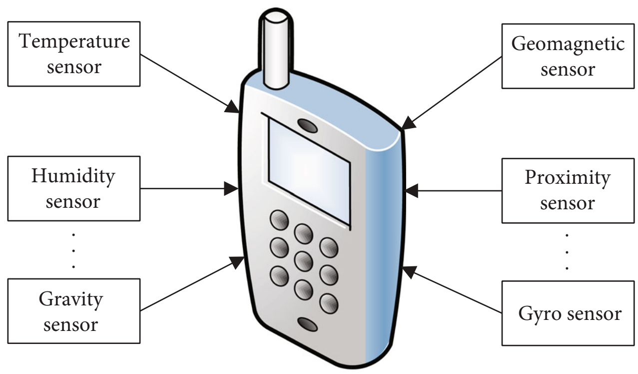

Figure 1: Common sensors embedded in a smartphone.

2.1. Basic Theory of MCS. MCS uses ubiquitous smart devices as the basic sensing unit to realize distributed and cross-temporal and spatial sensing data collection, thereby completing large-scale and complex sensing tasks [12]. Taking a smartphone as an example, Figure 1 shows common embedded sensors.

MCS typically consists of a server platform, task requesters, and task participants [13–15]. As shown in Figure 2, the server platform is composed of server clusters in the data center, which are used for publishing sensing tasks, collecting sensing data, and processing sensing data and other services. The role of task requesters is to send task requests to the server platform; the role of task participants is to collect various sensing data and use network communication technology to transmit sensing data [16–18]. The workflow of MCS includes the following stages [19–30]:

(1) The sensing task requester sends a task service request to the server platform, and the server platform publishes sensing service requests to sensing task participants. In addition, the server platform adopts corresponding incentive mechanisms to attract participants to participate in the sensing task [19, 20]

(2) Participants choose whether to participate in the sensing task based on their own sensing costs and the benefit of completing the sensing task after obtaining the sensing task information published by the service platform [21, 22]

(3) After obtaining the assigned sensing tasks, the sensing task participants use the sensing devices, which they carried to collect sensing data and forward it back to the service platform through network communication technology [23–26]

(4) After receiving the sensing data delivered by the sensing task participants, the service platform aggregates and processes the sensing data and provides it to the sensing task requester [27, 28]

(5) The service platform distributes the corresponding rewards based on the contributions of participants or the quality of the sensing data [29, 30]

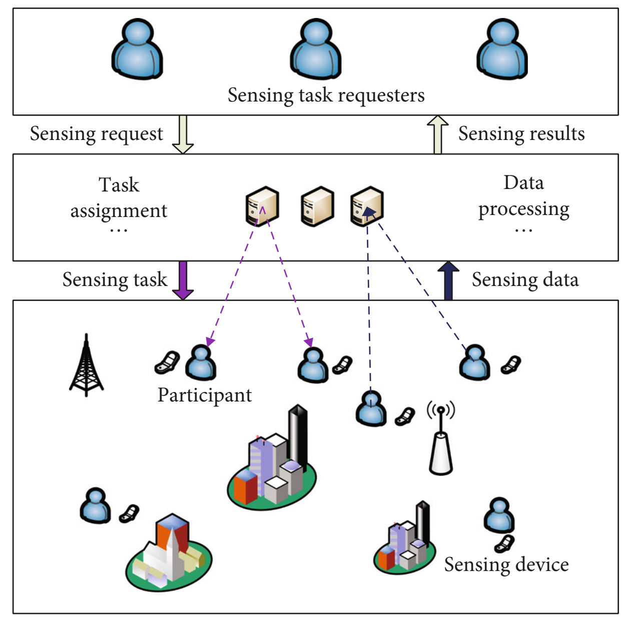

Figure 2: MCS framework.

2.2. Application of MCS. With the rapid development of handheld smart devices and communication technology, MCS has become one of the most important ways to collect sensing data. MCS has a very broad development space and has been widely used in various fields. The main applications include the following.

2.2.1. Environmental Monitoring. The MCS system uses sensor devices carried by sensing participants to sense various environmental information in the target area, such as air quality, weather, and noise. In terms of sensing air quality data information, literature [17] proposed an air quality monitoring program that uses air quality sensors carried by users to measure air pollution in their surroundings to provide a theoretical basis for the control of pollution. To measure air quality in a fine-grained and real-time manner, Devarakonda et al. [18] proposed a vehicular-based mobile sensing method. The method consists of two mobile platforms, one of which is a mobile sensing box, which is used deployed in public transportation, and the other is a personal sensing device that can be used for social pollution sensing. In addition, Gao et al. [19] proposed a low-cost mobile sensing method to monitor air quality. This method uses the POI-oriented bus selection algorithm to select buses for participation in environmental sensing activities and deploys air quality sensors on these buses to increase the coverage. In terms of sensing weather and noise data, in literature [20], Niforatos et al. proposed a hybrid crowdsourcing approach to estimate weather. This method uses sensing data collected by sensing devices to evaluate and predict future weather. In literature [21], Rana et al. designed an end-to-end noise mapping system based on MCS. This system uses sensing equipment to measure environmental noise and gather a large amount of user sensing data to construct a city's environmental noise map.

2.2.2. Smart Transportation. The MCS system uses sensor equipment carried by users or vehicles to sense the road conditions of a city. For instance, literature [22] proposed a pothole patrol system that obtains sensing data collected by vibration and GPS sensors to evaluate road surface conditions. Mohan et al. [23] monitor road and traffic conditions based on the mobility of smart device carriers and various sensors embedded in smart devices. Biagioni et al. [24] use a smartphone equipped with a map application to collect GPS trajectory information, thereby tracking, matching, and predicting the trajectory and arrival time of a vehicle. Yan et al. [25] proposed a method for monitoring urban traffic congestion based on cloud computing and MCS. This method obtains sensing data from a smartphone carried by the driver and provides a theoretical basis for controlling traffic congestion based on these data. Based on the idea of MCS, Wang et al. [26] studied how to extract actual road traffic information from the reports of a large number of unknown contributors.

2.2.3. Behavior Evaluation and Incident Discovery. The data information sensed by the MCS system can be used to evaluate various human behaviors or predict and discover certain incidents in a timely manner. For instance, Bengtsson et al. [27] established a model for estimating crowd behavior and reactions when disasters occur by analyzing the data on people's behaviors sensed by users when an earthquake occurs. In literature [28], Lee et al. proposed a geosocial event detection method based on a large number of geotagged Twitter messages to detect whether an area is in an abnormal state. In literature [29], Weppner and Lukowicz proposed a Bluetooth technology-based method for evaluating crowd density. This method uses information such as the link structure between actively scanning Bluetooth devices, the number of devices seen by a Bluetooth scan, teamwise diversity of discovered devices, and ratio of discovered devices in the current scan window to previous scan windows to evaluate population density.

2.2.4. Social Service. The data and information sensed by the MCS system can be used to improve urban management and planning. For example, in literature [30], Mathur et al. proposed a parking space statistics system. The system is based on a passenger-side-facing ultrasonic range finder and a GPS receiver to determine parking spot occupancy. In literature [31], Wenqian Nan and Bin Guo proposed a campus activity information collection and sharing system based on MCS. The system collects sensing data through smartphones to help students obtain timely, efficient, and comprehensive campus activity information. In literature [32], Karamshuk et al. chose a better geographic location for new retail stores based on the population's mobile pattern and geographic information.

2.2.5. Indoor Positioning. The data and information sensed by the MCS system can also be used for indoor positioning. For example, in literature [33], Gao et al. proposed a floor reconstruction system that collects information, such as location, size, and direction, and combines the user's movement trajectory and the locations where images are taken to complete floor plans with hallway connectivity, room sizes, and shapes. In literature [34], Zhang et al. proposed an indoor navigation system that includes three components, namely, map generation, localization, and navigation, where map generation is implemented based on crowdsensing theory. In literature [35], Teng et al. proposed an indoor-outdoor navigation service based on MCS technology. The service enables passengers to easily deploy indoor and outdoor navigation services for subway transportation systems.

3. Key Technology of MCS

In the field of MCS research, task allocation and incentive methods have received extensive attention from researchers. In this section, we summarize the research status of these two topics.

3.1. Task Allocation Method. The assignment of sensing tasks to sensing task participants is one of the main tasks of MCS systems [36–73]. In this section, we summarize existing research on task allocation methods from the following aspects: time, space, cost, benefit, and privacy.

3.1.1. Task Allocation Methods considering Time and Space Factors. Task allocation methods that consider the time factor include the following. In literature [36], Xiao et al. studied how to allocate tasks in a social network environment and proposed two algorithms for online task allocation and offline task allocation. Both algorithms can minimize the average makespan. In literature [37], Yao et al. studied how to minimize the task allocation time in MCS system. Based on historical encounter information and real-time task allocation time, they proposed offline and online task allocation methods. In literature [38], Li and Zhang studied the multitask assignment problem with time constraints. In this paper, the problem is first modeled as a combinatorial optimization problem with two time constraints, aiming to maximize the utility of the MCS platform. On this basis, two heuristic methods are proposed to overcome this issue.

Task allocation methods that consider the space factor include the following. According to the uncertainty of the location and the trajectory of the participants in MCS system, in literature [39], Pournajaf et al. designed a model for spatial task allocation. The model is based on a dynamic and adaptive data-driven method to allocate moving participants with uncertain trajectories to sensing tasks in a nearly optimal way. In addition, Pournajaf et al. also discussed the problem of spatial task allocation when workers use spatial cloaking to obfuscate their locations in literature [40]. In this literature, they proposed a two-stage optimization algorithm to obtain a feasible solution. In literature [41], He et al. studied the problem of assigning location-dependent tasks by considering the spatial movement constraints of sensing task participants and the geographic characteristics of the sensing task. On this basis, to obtain an approximate optimal solution to the problem, they proposed a task allocation mechanism based on the local ratio, which decomposes the problem into several subproblems by modifying the reward function in each iteration.

In literature [42], Zhang et al. proposed a user selection framework. This framework first predicts the coverage probability of users based on their historical records. On this basis, this framework computes the joint coverage probability of multiple users as a combined set and selects the near-minimal set of uses. In literature [43], Xiong et al. proposed a task allocation framework. This framework first predicts the call and mobility of mobile users based on their historical records. On this basis, this framework selects a group of users in each sensing cycle for piggyback crowdsensing task participation so that coverage quality close to the maximum can be obtained without exceeding the incentive budget. In literature [44], Tao and Song proposed a task allocation algorithm based on the clustering effect. In the process of designing the algorithm, not only how to maximize the data quality and the profit of workers are considered but also the clustering effect of tasks and the impact of different geographic distributions of tasks. In literature [45], Wu et al. analyzed the possibility of applying crowdsensing technology for sweep coverage. They proposed a framework to solve how to arrange workers to sweep large-scale target areas under dynamically changing quality requirements.

Literature [46] is aimed at maximizing the total task quality under the constraint of worker travel distance budgets. Gong et al. proposed location-based task allocation and path planning methods and designed a travel-distance-balance-based method, task-density-based method, bioinspired travel-distance-balance-based method, and quality-based method. All four methods work online to assign tasks when new work arrives. In literature [47], in terms of how to allocate each task to appropriate participants, Zhao et al. proposed a destination-aware task allocation method. This method uses a tree-decomposition algorithm to separate participants into independent clusters and utilizes a depth-first search method to prune nonpromising assignments. In literature [48], Tan et al. proposed a three-phase task allocation method for multiple cooperative tasks. This method uses real-life relationships to form compatible groups and increases task coverage through group-oriented cooperation while achieving good task cooperation quality.

In some research literature, space-time factors are also considered. In literature [49], Reddy et al. proposed a task allocation framework to efficiently complete a sensing task. In the process of designing the framework, the time and space factors and the behavior habits of the participants were considered. In literature [50], Cardone et al. proposed a crowdsensing platform, the platform profile users based on time, location, and social interaction. Then, participants are autonomously selected based on a matching algorithm to maximize sensing quality. According to the question of how to use a limited number of heterogeneous sensing vehicles to continuously collect comprehensive spatiotemporal sensing data, Liu et al. [51] proposed a sensing vehicle selection method. In this method, a utility function is designed based on the spatial distribution of the sensing vehicle and the sensing interface and the temporospatial coverage of the collected sensing data to estimate the sensing ability of the vehicle. The mapping of sensing tasks and mobile vehicles is realized based on the utility of the vehicle and the restriction of the number of recruited sensing vehicles.

In literature [52], Karaliopoulos et al. proposed a worker recruitment algorithm that translates the statistics of individual worker mobility to statistics of spacetime path formation. Then, the recruitment of participants is realized under the premise of ensuring the sensing coverage and minimizing consumption. In literature [53], according to the problem that sensing tasks are location-dependent and have time features, Yang et al. proposed a heterogeneous task allocation algorithm to ensure sensing quality. In literature [54], Zeng et al. proposed a task allocation framework based on the multisecret sharing method to preserve location privacy in task allocation. In the process of task allocation, tasks and participants are required to provide secret sharing of their real location information to fog nodes. On this basis, the paper also considered time-oriented and distance-oriented task allocation optimization and proposed an adaptive top-k-based participant selection method to select participants. In literature [55], Wei et al. proposed a task allocation framework based on subarea division learning, which uses an iterative self-organizing data analysis method to perform uneven subarea division considering historical data and spatiotemporal correlations. On this basis, the most suitable cells and participants are selected.

In literature [56], to minimize the total incentive budget and maximize data quality, Wang et al. proposed a two-stage task allocation method based on the implicit spatiotemporal correlations among heterogeneous tasks. To enhance the efficiency of allocation search, a decomposition and combination framework was designed to accommodate large-scale problem scenarios. In literature [57], Yucel and Bulut proposed a task assignment algorithm based on dynamic programming, which comprehensively considers worker preferences and the influence of each task assignment on the long-term utility of participants given the spatiotemporal characteristics of tasks. In literature [58], Zhang J. and Zhang X. proposed a task assignment method based on mobility prediction to assign appropriate sensing tasks to participants. This method selects suitable participants for task assignment by considering the participants' historical movement trajectory and the time and space characteristics of the task. In literature [59], Wang et al. proposed a participant recruitment mechanism for time-sensitive and location-dependent tasks. This mechanism combines spatiotemporal context information with content information to characterize participants' preferences for tasks in mobile crowdsensing systems, thereby improving the accuracy of participant recruitment.

3.1.2. Task Allocation Methods considering Costs and Benefits. Costs and benefits are important factors to consider in the process of designing task allocation methods. In the MCS system, the minimum sensing cost and the maximum sensing benefit are usually considered as optimization goals [60–68].

In literature [60], Pham et al. proposed a participant selection method based on an evolutionary algorithm that can obtain high-quality and low-cost data from participants. In literature [61], Wang et al. proposed a multisensor task scheduling algorithm that formalized the minimum energy multisensor task scheduling problem as an integer linear programming problem and provided a heuristic solution to minimize energy consumption under the premise of guaranteed sensing quality. In literature [62], with the goal of minimizing the allocation cost and satisfying fairness, Liu et al. modeled each worker's processing ability as a worker processing queue and converted the constraint of task assignment frequency to task virtual queues. The Lyapunov optimization was used to control actions in each time slot. In literature [63], Yucel and Bulut proposed a user-satisfaction-aware task allocation method to maximize system utility and user satisfaction simultaneously. Since the problem is NP-complete, the authors first solved the problem via integer linear programming and supplied two heuristic-based polynomial solutions. In literature [64], Yucel et al. proposed a task allocation method to address the conflict between the coverage preferences of service requesters and the profit preferences of budget-constrained participants.

In addition, when designing task allocation methods, some researchers consider not only cost or benefit factors but also time or space factors.

In literature [65], Song et al. proposed a multitask-oriented participant selection method that can collect the maximum amount of sensing data in the time and space dimensions for all sensing tasks under budget constraints. In literature [66], Li et al. proposed a dynamic participant recruitment algorithm to select participants to perform sensing tasks under certain constraints. This algorithm minimizes the cost of sensing while maintaining a certain level of probabilistic coverage. In literature [67], Wang et al. proposed a task allocation framework that combines Bayesian inference, compressive sensing, and active learning to dynamically select a minimum number of subareas for task allocation. This method reduces the corresponding budget while ensuring the sensing quality. In literature [68], Xiong et al. defined a spatiotemporal coverage metric, named k-depth coverage that considers two factors, namely, the number of sensor readings collected in each covered subarea and the proportion of subareas covered by sensor readings. A task allocation framework that enhances the efficiency of sensing data collection without increasing consumption was then proposed.

3.1.3. Task Allocation Methods considering Privacy. In the process of task assignment and data collection, the MCS system collects detailed sensing data from users, which undoubtedly poses a threat to the privacy of users [69–73]. In literature [69], Wang et al. proposed a task assignment framework that protects location privacy by obscuring participants' reported locations under the guarantee of differential privacy. In literature [70], Wu et al. proposed a privacy-aware task allocation mechanism. They first presented a fog-assisted architecture that can help the spatial crowdsourcing server allocate tasks and aggregate sensing data in a privacy-aware manner. On this basis, they proposed a privacy-aware task allocation and sensing data aggregation mechanism that provides strong privacy protection.

In literature [71], Wang et al. proposed a personalized privacy-preserving task allocation framework. Each participant in the sensing task uploads their personal privacy level and obfuscated distance to the server rather than their true distance or location. In literature [72], Zhao et al. proposed a bilateral privacy-preserving task allocation method that cannot only protect the privacy of task participants but also protect the privacy of task requesters and minimize travel distance. In literature [73], Wang et al. proposed a task allocation algorithm that performs task allocation based on the mapping accuracy of sensing tasks and participants while preserving participants' location privacy. This algorithm cannot only protect the privacy of participants but also effectively enhance the overall performance of the crowdsensing system.

3.2. Incentive Methods. In the MCS system, incentives can effectively motivate workers to participate in sensing tasks [74–95]. In this section, we summarize the existing research on incentive methods from the following aspects: cost, benefit, privacy, and quality.

3.2.1. Incentive Methods considering Costs and Benefits. In the MCS system, the budget is usually relatively limited, so cost and benefit are key factors to consider when designing an incentive method [74–86]. Some incentive methods are designed based on auction mechanisms. For example, in literature [74], Jaimes et al. proposed a recurrent reverse auction incentive method that uses a greedy mechanism to choose a representative subset of users based on location under a given fixed budget. In literature [75], Zhao et al. proposed an online incentive method based on an online auction, in which participants report their strategic profiles to the crowdsourcer in an online mode. The crowdsourcer then selects participants to complete a specific number of sensing tasks before the deadline while minimizing the total payment. In literature [76], Zheng et al. considered budget feasibility in designing an incentive method. They first modeled the weighted coverage maximization under different coverage requirements in MCS as budget-limited reverse auctions. On this basis, a deterministic method for maximizing weighted coverage in MCS was proposed and theoretically shown to improve performance.

In literature [77], because users have heterogeneous sensing costs in different regions of interest, Zhang et al. designed two optimization models to characterize the quality of service for MCS applications. They proposed a budget-limited incentive mechanism based on reverse auctions, thereby maximizing the numbers of recruited users and the utility functions for all regions of interest across the sensing area. In literature [78], Liu et al. proposed a monetary-based incentive method. In the article, they proposed two system models for single tasks and multiple tasks. In the single-task-oriented model, an incentive method was designed based on game theory, and it was proven that a Nash equilibrium exists. In the multi-task-oriented model, an auction-based incentive method was proposed, and it was proven that the incentive method has the desirable properties of truthfulness, profitability, individual rationality, and computational efficiency. In addition, while designing the incentive method, the utility maximization problems of the workers and crowdsourcer are simultaneously considered.

In literature [79], Wang et al. proposed a social awareness reverse auction mechanism for how both the platform and participants can obtain the greatest benefits when the budget is limited. In this mechanism, the total contribution of participants is the key to choosing winners, and the winners are paid based on critical prices. In literature [80], Wang et al. proposed an incentive method for budget-constrained mobile crowdsensing systems. They presented a reverse-auction framework to model interactions between workers and the platform. Moreover, an online incentive mechanism was proposed to motivate users based on remuneration determination and online winner selection strategies.

In addition, in literature [81], Zhao and Liu proposed an incentive method for vehicular crowdsensing. To maximize the overall utility of the vehicle driver, deep reinforcement learning technology was used to derive the optimal long-term sensing strategy for all vehicles. In literature [82], Li et al. proposed a point-of-interest- (POI-) tagging app-assisted incentive method that models the interactions of users, platforms, and apps through a three-stage decision process. The app first determines the POI-tagging price to maximize the payoff. The platform and the user then decide how to determine the task reward and choose edges to be tagged and how to choose the best task to perform, respectively.

In literature [83], Nie et al. proposed an incentive method that formalized the social influence of users and the strategic interconnections of service providers into a game model. The model optimizes the players' decisions to achieve their individual objectives to maximize the profits of service providers and maximize the utility of users. In literature [84], Li et al. designed an incentive method for crowdsensing under continuous and time-varying scenarios. First, the incentive problem is modeled as a three-stage Stackelberg game. On this basis, the method uses the Lyapunov optimization to solve the issue of users' long-term participation and guarantee the platform's profit. In addition, the method calculates the users' interests in tasks based on the computing capabilities of their mobile devices.

In literature [85], Han et al. proposed an incentive method for the MCS scheduling problem. In this article, the owner of a mobile crowdsensing application publishes sensing tasks; then, participants compete for sensing tasks based on their respective available time periods and sensing costs. Finally, the task publisher schedules and pays participants to maximize its own sensing revenue under a certain budget. In literature [86], Ji and Chen proposed an incentive method for MCS, where each participant has a uniform sensing subtask length. Furthermore, the authors prove that this mechanism can achieve perfect Bayesian equilibrium and maximize platform utility.

3.2.2. Incentive Methods considering Privacy. In the MCS system, the privacy factor must also be considered in the process of incentive method design. In literature [87], Jin et al. proposed an incentive method for MCS that chooses participants who are likely to supply reliable data and compensates them for the cost of privacy and sensing leakage. In literature [88], according to most existing incentive methods, only consider how to compensate participants' sensing cost, and the cost incurred by potential privacy leakage is ignored. Sun et al. proposed a contract-based personalized privacy preserving incentive method that supplies personalized payments for participants as compensation for privacy costs while achieving accurate truth discovery.

In literature [89], Liu et al. proposed an incentive method based on game theory and deep learning. The goal of this method is to ensure the availability of sensing data and maximize the utilities of the platform and participants while protecting the privacy of participants. In literature [90], Zhao et al. proposed a privacy and reliability-aware real-time incentive system that simultaneously solves the three problems of incentive method design, privacy preservation, and data reliability estimation. The system can effectively solve the problems of workers' calculation and communication costs and unfair reward distribution.

3.2.3. Incentive Methods considering Quality. In the MCS system, quality factors are also considered in the process of designing incentive methods. In literature [91], Jin et al. added users' quality of information as a key indicator to the design of the incentive mechanism and proposed an incentive method based on reverse combinatorial auctions. This mechanism enables the platform to obtain high-quality data at a very low cost. In literature [92], Hou and Pei proposed an incentive method for video collection. This method introduces multiple parameters to evaluate the quality of the collected data. Based on the social relationships of participants, they proposed a social-aware incentive method to achieve full-view coverage for a target by efficiently collecting video clips. Moreover, the method satisfies the characteristics of truth, individual rationality, and computational efficiency.

In literature [93], Liu et al. proposed an incentive method based on behavioral economics. The mechanism consists of two components, namely, participant selection and payment decision. This mechanism can effectively motivate participants to complete sensing tasks in areas with sparse participants, thereby ensuring the completion rate of the tasks. In literature [94], Zhao et al. proposed an incentive method based on privacy preservation and quality awareness that can preserve data privacy while evaluating data reliability. In addition, data quality is quantified based on the deviation between the ground truth and reliable data. Finally, the method assigns monetary rewards to task participants based on the quality of data they provide. In literature [95], Fang et al. proposed an online incentive method oriented to social crowdsensing networks. To maximize the accumulated social welfare achieved by the network, the authors designed a user selection mechanism and payment determination mechanism. The article considered two aspects when paying participants: data quality and social influence.

4. Other Key Technologies in MCS

In the MCS system, data forwarding, sensing quality assurance, and evaluation have also been studied by many researchers. In this section, we summarize these three parts.

4.1. Data Transmission Methods. In the MCS system, efficient data forwarding methods can effectively guarantee the sensing quality [96–102]. In literature [96], to build sensing maps satisfying specific sensing quality with low energy consumption and delay, Zhao et al. proposed a cooperative sensing and data forwarding framework. They presented two cooperative forwarding mechanisms by leveraging data fusion. These two forwarding mechanisms are epidemic routing with fusion and binary spray-and-wait with fusion. Cooperative forwarding mechanisms can obtain a satisfactory tradeoff between delay and overhead. In literature [97], Higuchi et al. proposed an information diffusion method for sensing data collection through an opportunistic network. This method first detects groups of pedestrians based on the history of radio connectivity information between mobile users and maintains a local network. On this basis, this method collaboratively performs neighbor discovery and link management with the local network members to improve the energy efficiency of neighbor discovery and minimize transmission delay.

In literature [98], Wang et al. proposed a method to evaluate a node's data forwarding ability. The paper first determines whether the encountered node is able to forward data to the destination and then calculates the probability of the node forwarding data to the destination based on the intercontact time distribution. Only nodes with high metric values can carry data. In literature [99], to obtain energy-efficient transmission, Xiao et al. proposed a data transmission protocol that deploys static nodes based on the "Archimedes-curve" model to aid data forwarding.

In literature [100], Jung and Baek proposed a multihop sensing data forwarding algorithm for crowdsensing networks. A main feature of this algorithm is the abbreviation of an intermediate node's address. In addition, in terms of latency and delivery ratio, the algorithm can obtain better network performance. In literature [101], Ghafoor et al. proposed a routing algorithm based on fuzzy logic. The algorithm combines human social behavior, link quality, and node quality to make routing decisions. Furthermore, the algorithm uses the signal-to-noise ratio to ensure good link quality node selection, a friendship mechanism for trust management, and the remaining energy for long-lasting sensor lifetime.

In literature [102], Peng et al. proposed a data transmission method based on the city public transportation system that selects mobile nodes to transmit data by maximizing the incremental transmission utility. This paper makes full use of the advantages of buses in public transportation systems to realize the rapid transmission of large-scale sensed data. In literature [103], He et al. proposed a spatiotemporal opportunistic transmission algorithm that defines spatiotemporal encountering and visiting parameters. On this basis, the algorithm searches publishers or participants of sensing tasks based on the spatiotemporal encountering parameters and tracks the publishers or participants based on the spatiotemporal visiting parameters to realize reliable opportunistic transmission across regions and time intervals.

4.2. Sensing Quality Assurance and Evaluation Methods. Sensing quality is a measure of sensing results that is used to quantify the degree of satisfaction of users with sensing information [104–108]. In literature [104], Vergara-Laurens et al. proposed a hybrid privacy-preserving method based on data obfuscation, anonymization, and encryption techniques to guarantee the quality of information and privacy protection without increasing energy consumption. In literature [105], according to the contradiction between sensing cost and sensing quality, Wang et al. proposed a sparse crowdsensing paradigm. The paradigm uses the spatiotemporal correlation among data sensed in different subareas to reduce the required number of sensing tasks. This paradigm guarantees the sensing quality and effectively reduces the sensing cost. In literature [106], Marjanović et al. proposed a framework for green MCS. This framework can effectively eliminate redundant sensor activity while meeting sensing coverage requirements and sensing quality and consequently reduces the overall energy consumption of an MCS application.

In literature [107], An et al. proposed a crowdsensing quality control model based on a two-consensus blockchain. The article introduces the idea of a blockchain into a quality control model. On this basis, a credit-based verifier selection method and a two-consensus method are proposed to achieve the nonrepudiation and nontampering of information in crowdsensing. Finally, the article proposes node matching and quality grading evaluation methods to help task publishers obtain high-quality sensing data. In literature [108], Liu et al. designed a social team crowdsourcing framework for social Internet of Things systems. To design the framework, they introduced the trust relationships between nodes into the quality evaluation of the sensing data. Then, they proposed a task allocation algorithm in which the sensing quality guides the participant selection to maximize the overall task valuation under a budget constraint.

5. Conclusions and Future Work

MCS uses ubiquitous smart devices and network access technology to migrate sensing tasks from a centralized platform to a distributed computing terminal across time and space and provides a new approach to solving large-scale, diversified, and complex sensing problems. This article summarizes the current research progress of MCS to promote attention and research of this emerging technology by scholars in related fields. We expect that the key research directions of MCS in the future will include the following: (1) research on hybrid network application systems that combine positioning technology, edge computing technology, etc.; (2) research on general task allocation methods to address large-scale and uncertain sensing environments; (3) research on cross-layer incentive methods based on the architecture of MCS to handle uncertain sensing environments; (4)

research on efficient sensing data transmission methods based on cloud computing and vehicle network theory; and (5) research on multiobjective optimization methods in large-scale sensing environments based on related technologies in the field of big data to guarantee the quality of sensing data.

Data Availability

No data were used to support this study.

Conflicts of Interest

The author declares that there is no conflict of interest regarding the publication of this paper.

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