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Task Allocation in Mobile Crowdsensing for Smart Agriculture: A Survey

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Abstract: Mobile Crowdsensing (MCS) serves as a scalable data acquisition paradigm for smart agriculture, supporting a range of applications from soil monitoring to crop assessment. A core challenge lies in efficiently allocating sensing tasks to distributed participants (e.g., farmers), which directly impacts task execution efficiency, cost control, and overall system effectiveness. This paper provides a systematic review of MCS task allocation methods for agricultural scenarios, covering classical greedy strategies, evolutionary algorithms, and others, aimed at addressing practical constraints such as dynamic field environments and limited resources. By synthesizing existing research, this survey summarizes current trends, identifies unresolved issues, and proposes future directions for developing more robust task allocation mechanisms, with the goal of fully leveraging the potential of MCS in precision agriculture.

Keywords: Mobile crowdsensing; Task allocation; Smart agriculture; Data collection

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1. Introduction

The proliferation of smartphones has given rise to Mobile Crowdsensing (MCS)—a flexible and low-cost new paradigm for data collection [1]. However, its application remains largely concentrated in the field of smart cities, while practical adoption in smart agriculture is still limited. Although existing research has explored the use of MCS as a supplement to current systems such as the Space-Air-Ground Integrated Network (SAGIN) for agricultural tasks like pest and disease monitoring, both real-world implementation and targeted research in this area require further expansion [2].

The core challenge of applying MCS in smart agriculture lies in designing task allocation mechanisms that align with agricultural characteristics. Most existing solutions are tailored to urban scenarios and struggle to accommodate the unique spatiotemporal correlation, growth periodicity, and continuous monitoring demands inherent in agricultural data [3]. Moreover, the majority of studies focus on single-objective optimization and lack an integrated framework capable of simultaneously addressing dynamic participant matching, heterogeneous data quality assessment, and quality-driven incentives. Therefore, there is an urgent need to develop dedicated task allocation methods for agricultural scenarios in order to fully unleash the potential of MCS in advancing precision agriculture. This paper aims to review current trends, identify key shortcomings in existing research, and propose future directions for the field.

2. Basic theory of mobile crowdsensing

A general MCS framework encompasses three primary entities: the service provider, task requesters (data requesters), and mobile users (workers/participants) [3]. These entities engage in interaction and collaboration according to the MCS framework. The lifecycle of an MCS system comprises four stages: task generation, task allocation, task execution, and data collection. The main functionality and research issues of each stage are briefly described as follows (depicted in **Figure 1**):

Figure 1. MCS framework

2.1. Task generation

Task requesters, constrained by resources, are unable to collect data themselves and must submit detailed requirements—including spatiotemporal scope, volume, and budget—to the service provider. The core challenge for the service provider lies in efficiently creating and publishing sensing tasks to achieve precise matching between supply and demand.

2.2. Task allocation

After publishing MCS tasks, the provider must allocate them effectively by recruiting suitable workers. The core challenge is to achieve optimal allocation through strategies that balance spatial-temporal constraints, user-task dynamics, incentives, energy use, and platform benefits. The allocation outcome directly impacts service quality, provider reputation, and user satisfaction.

2.3. Task execution

After receiving the assigned sensing tasks, workers need to complete the tasks within a predetermined time and space range, that is, a specified duration and a designated target area. This process covers multiple aspects such as data collection, data processing, and data storage. At this stage of execution, the core challenge faced by workers is how to effectively save energy consumption to maximize profits while ensuring task completion.

2.4. Data collection

Upon task completion, workers submit data to the platform. The service provider must integrate this data, allocate fair rewards based on evaluated data quality, and provide precise feedback to the requester. Accurately assessing data quality and stimulating sustained user engagement are central challenges at this stage.

This study mainly focuses on key issues such as allocation strategies during the task allocation stage, aiming to explore effective solutions and make positive contributions to the theoretical and technological expansion of MCS in the field of intelligent agriculture.

3. State-of-the-art of task allocation for mobile crowdsensing

Task allocation, a core MCS mechanism, matches tasks to optimal workers. This section reviews key research from five perspectives.

3.1. Task allocation model

Task allocation in MCS, categorized into online and offline models, is fundamental for selecting suitable mobile users and directly determines crowdsensing data quality.

3.1.1. Offline task allocation

In offline task allocation, the sensing platform possesses complete information about all tasks and available mobile users beforehand, formulating a comprehensive allocation plan before initiation.

Existing research has devised various offline mechanisms from different perspectives. For instance, Yu et al. developed an optimization model to ensure data coverage throughout the target period by minimizing overall personnel costs [4]. Guo et al. differentiated strategies based on task urgency: for time-sensitive tasks, they optimized for minimal user travel distance to accelerate completion, while for less critical tasks, they leveraged historical user trajectories to assign tasks opportunistically, minimizing user disruption [5]. Data quality is another core consideration. Song et al. defined data quality metrics based on completeness and volume, seeking to optimize them under a given budget [6]. Alternatively, Wang et al. predicted user task preferences by analyzing their historical records to achieve a more precise user-task match [7].

Offline allocation offers comprehensive planning but lacks flexibility, as it cannot adapt to newly arriving users or tasks.

3.1.2. Online task allocation

Online task allocation in MCS dynamically matches real-time tasks with suitable users based on spatiotemporal constraints, device capabilities, and willingness, thereby improving responsiveness and satisfaction beyond the limits of offline methods.

Several studies have advanced online allocation strategies under different constraints. Zhao et al. proposed a multi-stage threshold-based method to select high-utility users within a limited budget [8]. Similarly, Gao et al. designed a quality-driven incentive mechanism that divides the sensing process into stages, allocating basic and bonus rewards to promote sustained participation and high-quality data submission [9]. Li et al. focused on scenarios with dynamically generated tasks, using historical data to estimate user mobility and selecting executors to maximize spatiotemporal coverage [10]. Wang et al. applied a Lyapunov optimization-based approach to handle dynamic task appearances and user movements, achieving near-optimal average sensing utility [11].

Online allocation excels in dynamic settings but requires efficient, real-time processing. Developing scalable and adaptive frameworks is key to advancing MCS performance.

3.2. Optimization objective of task allocation

According to different optimization objectives, MCS task allocation can be mainly divided into two categories: single-objective optimization allocation and multi-objective optimization allocation. Both of these are current research hotspots and difficulties, and face some common challenges.

3.2.1. Single-objective optimization allocation

Single-objective task allocation focuses on optimizing one primary goal, often solved with greedy or heuristic methods due to its NP-hard nature.

Several frameworks have been developed to address specific optimization goals. Xiong et al. proposed EMC3, which minimizes both the number of assigned tasks and energy consumption by predicting user mobility to ensure area coverage [12]. Wang et al. introduced MTPS, a fine-grained allocation framework that maximizes overall data quality under a shared budget by employing an attention-based incentive model to compensate for users' task-switching burdens [13]. Similarly, Zhang et al. designed CrowdRecruiter, which selects a near-minimal set of participants to meet probabilistic coverage constraints, thereby minimizing incentive costs [14]. Other approaches address data collection efficiency. Majeed et al. developed a hybrid scheme leveraging both cellular and opportunistic networks to ensure high data transmission probability at low cost [15]. Karaliopoulos et al. transformed user selection into a minimum cost set coverage problem, utilizing individual mobility statistics to form spatiotemporal paths cost-effectively [16].

In summary, single-objective optimization offers clear goals, high efficiency, and straightforward evaluation. However, its primary limitation lies in its lack of flexibility, as focusing on a single metric may overlook other critical factors like user satisfaction and system robustness, potentially leading to suboptimal overall performance.

3.2.2. Multi-objective optimization allocation

Multi-objective optimization in task allocation balances conflicting goals using methods like weighted combination or Pareto optimization.

Several studies demonstrate innovative solutions to these challenges. Li et al. addressed spatiotemporal coverage tasks with limited participants through constraint-based greedy algorithms (GMaxEOQU and GMinEOIP) and a Pareto-based Particle Swarm Optimization, effectively balancing quality, utility, and incentive costs [17]. Ji et al. framed task allocation as a dynamic multi-objective problem, employing a Generative Adversarial Network to rapidly generate Pareto-optimal solutions that account for user spatial preferences [18].

Recent research has expanded to address practical limitations. Shen et al. developed a variable-speed multi-task allocation model that maximizes user rewards while minimizing completion time, using a shuffled frog leaping algorithm to overcome the reputation bias in task assignment [19]. Privacy concerns have also gained attention, with Peng et al. proposing a differential privacy-based scheme using NSGA-II to optimize travel distance and publisher costs, while Lin et al. introduced secure protocols for quality calculation and user recruitment that protect sensitive information while maintaining sensing quality [20–21].

While multi-objective optimization enables comprehensive system optimization and enhanced decision-making, it demands substantial computational resources and careful management of solution diversity. The effectiveness of these approaches ultimately depends on properly balancing competing objectives and addressing implementation challenges in practical scenarios.

3.3. Task allocation algorithm

Task allocation in MCS is an NP-hard combinatorial optimization problem. While exhaustive search is impractical, research focuses on approximate algorithms, primarily categorized into greedy and non-greedy strategies, to achieve near-optimal solutions efficiently.

3.3.1. Greedy-based algorithms

Most current MCS task allocation research relies on greedy-based algorithms [22–24]. These iteratively select the most advantageous element (worker or task-worker pair) and add it to a set until a termination condition is met, like budget exhaustion or full coverage. The resulting set is then considered near-optimal. For example, Song et al. chose participants for maximum coverage [6]. Literature preassigns tasks and uses greedy descent to delete tasks contributing least to sensing quality under workload constraints [11]. Wang et al. design a greedy algorithm to maximize sensing quality within budget, selecting executors with the highest sensing ability-to-cost ratio [13]. Literature ignores budget, aiming for the best sensing quality by recruiting users [25].

Although greedy algorithms may not always be able to find the global optimum, they have some significant advantages that make them highly effective in many application scenarios.

3.3.2. Non-greedy algorithms

While effective in specific settings, greedy algorithms often yield suboptimal solutions due to their local optimization nature. Consequently, more advanced methods have been developed to overcome these limitations in MCS task allocation.

Evolutionary algorithms (such as GA) are frequently applied to task allocation in Mobile Crowd Sensing (MCS), leveraging implicit parallelism to seek global optima. Yang et al. employed a GA to search for task assignment schemes with the shortest delay time, ensuring the timely completion of tasks [26]. This algorithm uses a multi-point crossover operator to exchange genes of parent generations to generate offspring, and helps the population jump out of local optima by swapping the positions of two different genes in the offspring. Tao et al. proposed a GA to maximize data quality and designed a Detective Algorithm (DA) to enhance workers' profits, taking workers' benefits into account [27]. Ipaye et al. presented a Worker Multi-Task Allocation-Genetic Algorithm (WMTA-GA) to assist workers in selecting multiple tasks while considering time constraints and task requirements, aiming to maximize workers' welfare [28]. Li et al. designed a novel crossover operator that combines high-quality gene fragments from two parents to generate excellent offspring [29]. They also devised a repair strategy to ensure the feasibility of the allocation plan. Tao and Song considered factors like task execution location, time window, user movement trajectory, and arrival time to construct an MCS task allocation model [30]. They used an ant colony algorithm to search for an allocation scheme that could complete all tasks on schedule and maximize the benefits of the sensing platform.

Recent advances in deep learning show that it can be trained to simulate the distribution of solutions of a given optimization problem in the decision space, and directly generate new solutions accordingly [31]. Xu et al. integrated a Graph Attention Network (GAT) into Deep Reinforcement Learning (DRL) and developed a GAT-based DRL method (GDRL) to solve an NP-hard task allocation problem [32].

Non-greedy algorithms offer global optimization, adaptability, and robustness, yet they face challenges in design complexity, implementation difficulty, and often lack interpretability due to intricate heuristic rules.

4. Challenges and opportunities in mobile crowdsensing

MCS networks, which leverage mobile users equipped with mobile terminal devices as sensing nodes, confront novel problems and challenges in comparison to traditional wireless sensor networks.

4.1. Difficulty in task allocation

In MCS systems, user sensing abilities vary and dynamically change as user location, joining, or leaving the system also changes over time. The sensing platform needs to comprehensively consider the time, space, accuracy, requirements of the task, as well as the user's sensing ability, incentive cost, and time-varying characteristics, and select a suitable subset from numerous users to complete the task. Therefore, reasonably modeling sensing tasks and mobile users for different scenarios, and designing efficient task allocation methods to achieve sensing quality optimization and cost reduction under limited resources, is an urgent problem that needs solving.

4.2. Incentive mechanism

MCS relies on the participation of a large number of mobile users. However, mobile users may lose their willingness to participate in sensing activities due to the consumption of their mobile device energy, communication resources, as well as the cost of moving to the destination sensing location, and the risk of privacy breaches they might face. Therefore, it is necessary to design efficient incentive mechanisms that provide reasonable rewards to each mobile user to compensate them for the cost of performing sensing tasks, in order to attract a large number of mobile users to continue participating in sensing activities, and to ensure the quality of sensed data.

4.3. Data integration and mining

The data of MCS comes from diverse mobile users, who use sensing devices with different accuracies, are in different collection environments, and are influenced by personal subjective cognition and participation willingness, resulting in significant differences in the quality of the collected data. Therefore, correcting and integrating such a large and uneven dataset to extract valuable information and refine effective knowledge is a prerequisite for the widespread application of MCS technology.

4.4. Privacy protection

Sensed data may carry private and sensitive information such as the location, movement trajectory, and lifestyle habits of mobile users. If leaked, it can cause great inconvenience to mobile users. Therefore, a reasonable privacy protection mechanism is the foundation for ensuring the long-term stable operation of MCS networks.

5. Conclusion

This survey systematically examines key dimensions of task allocation methods, including offline versus online models, single-objective versus multi-objective optimization, and greedy versus non-greedy (e.g., evolutionary) algorithms. While classical approaches lay the foundation, integrating diverse strategies is essential to address the dynamics and constraints of agricultural environments.

Several critical challenges remain: sustaining long-term participant engagement, ensuring system robustness amid agricultural uncertainties, and enabling scalable allocation for heterogeneous, large-scale operations. Future progress hinges on the development of adaptive, intelligent strategies that integrate artificial intelligence and Internet of Things technologies. By overcoming these bottlenecks, people can advance efficient and scalable task allocation mechanisms, thereby fully unlocking the potential of mobile crowd sensing in precision agriculture.

Disclosure statement

The authors declare no conflict of interest.

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