Mobile Crowdsensing

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1 Introduction

2 Related Works

Raghu K. Ganti et al. [4] gave a basic explanation of mobile crowdsensing. A brief discussion on the existing applications and research challenges was done. Every application was built independently with no common component. Sensitive sensor data pertaining to individuals was collected. Local analytics were used to process the raw data collected. It was a two-step process. First, he gave appropriately summarised data. Second, it reduced the amount of processing that the back end had to perform further. A generic perturbation technique was in need of being developed so that privacy and security could be achieved in a generic setting, independent of the nature of the data being shared. Leye Wang et al. [14] wanted to make sure the sensed data covered the full target area for a high quality sensed result in MCS. Sparse mobile crowdsensing made use of the spatial and temporal correlation between the data sensed in different sub-areas to lessen the total number of tasks assigned for sensing while maintaining data quality. With sparse MCS, fewer participants were needed for each application, allowing for the simultaneous operation of more. The Sparse MCS Framework's justification was that different urban sensing data have spatio-temporal correlations, making it possible to infer the missing information for unsensed spatio-temporal cells from sparsely sensed data. Wei Gong et al. [5] gave a survey of contemporary task assignment techniques for mobile crowdsensing in this article. Wei Gong et al. [5] concentrated on participatory sensing among the current works, where task assignment primarily aimed to arrange workers' travelling pathways to increase task quality while staying within each worker's trip cost budget. Wei Gong et al. [5] concentrated on opportunistic sensing, in which case the data collectors gathered sensing information along their pathways without interfering with their regular routines. Following an examination of opportunistic sensing-based mechanisms, Wei Gong et al. [5] turned to participatory sensing-based ones. He provided a thorough analysis of common task assignment methods for mobile crowdsensing. A variety of job assignment techniques had been developed in various contexts in an effort to improve work quality or reduce task costs. The list of possible research subjects in this area is far from complete.

Shihong Zou et al. [20] presented CrowdBLPS, a location-privacy-preserving mobile crowdsensing system that integrated the concept of blockchain into crowdsensing, to avoid security issues such as information repudiation and tampering from the conventional, centrally managed crowdsensing system. Following the idea of a smart contract, Shihong Zou et al. [20] proposed a two-stage approach including a preregistration stage and a final-selection stage based on spatial location privacy-preserving and greedy algorithms to protect workers' location privacy and reduce task cost while achieving the purpose of data quality control in the blockchain-based crowdsensing model. The use of fixed-location sensing techniques similar to wireless sensor networks had emerged as the primary mode of data collection as a more significant component of traditional IoT. However, in the majority of real-world circumstances, it was challenging for this conventional way of data collection to satisfy the variety of data sensing requirements. An urgent objective was to create a novel data collection strategy that differs from the conventional one. Jiejun Hu et al. [8] suggested a novel MCS framework based on blockchain technology that protected privacy and ensured the security of both the sensing process and the incentive mechanism. He suggests an incentive system supported by a three-stage Stackelberg game by examining two different types of participants and the task initiator. The evaluation examines two aspects: the performance of the blockchain-based MCS and the incentive mechanism, through theoretical study and simulation. When compared to a conventional Stackelberg game, the suggested reward method increases the task initiator's utility by up to 10 percent. It also achieved sustainable provisioning of sensory data while maintaining the necessary market share for participants who paid on a monthly basis. The analysis of the blockchain-based MCS revealed that as the participant count rose, the latency increased in a manageable way. Jinbo Xiong et al. [16] took into account the PERIO framework's system model in the context of a standard MCS architecture. A dynamic privacy protection approach could be used to measure the true privacy protection level that the system desires by dynamically modifying the privacy protection parameters to satisfy the privacy protection needed at different locations. For MCS services in the IIoT, Jinbo Xiong et al. [16] suggested the PERIO framework, which included a tailored privacy measurement method, a practical uploading technique, and a privacy-preserving data aggregation scheme. This framework promoted user utility, increased privacy levels, and complied with QoCS criteria. The overall advantages of the PERIO framework over the competing schemes in realistic circumstances were demonstrated by theoretical analysis and a wealth of simulation results utilising real trajectory datasets.

Sumudu Hasala Marakkalage et al. [10] outlined a mobile crowdsensing strategy to comprehend the everyday routine of Singapore's elderly population. in order to analyse the multisensor data (location, noise, and light) obtained from a smartphone application. He used novel clustering, sensor fusion, and user profiling techniques. As a result, he was able to determine the travel patterns at various points of interest (POI), the effects of travel frequency for particular

POI, and the three main user profiles. According to the findings, older people spend the majority of their free time in local food courts and community centers, though they travel elsewhere for healthcare and religious obligations. José M. Cecilia et al. [1] summarised the MCS research activities being carried out by the Spanish community to address the COVID-19 pandemic in Spain. He outlined the COVID-19 pandemic's history of development in Spain as well as the MCS research initiatives and technologies being created there to address the effects of the containment measures put in place to deal with the COVID-19 epidemic and to support epidemiological surveillance. The actions were severely harming the economy, jeopardising the welfare state in wealthy societies, and having very dismal predictions for developing economies. Fortunately, modern tools like MCS provided creative ways to design "smart" quarantine periods that provide social isolation without lockdowns. In order to implement this smart quarantine idea in Spain, new advances within the MCS framework have been briefly discussed in this study. Lei Shu et al. [12] had demonstrated that MCS can offer an adaptable, scalable, and affordable solution for industrial sensing when compared to the shortcomings of older methods in industrial settings. Lei Shu et al. [12] highlighted SPOON's security attributes and illustrated how effective it is for communication and computing. With SPOON, the service provider could choose the appropriate sensing reports depending on the trustworthiness of the users and attract mobile users based on their whereabouts without violating their privacy. Sensing tasks were safeguarded, and reports were anonymized to prevent privacy leakage using proxy re-encryption and BBS+ signatures. In order to enable decentralised trust management and safe credit evidence for mobile users, a privacy-preserving credit management system is also introduced.

Venkat Surya Dasari et al. [2] used Game Theory to explore how consumers might be incorporated into the MCS loop. Game theory provided a better strategy in a situation where competition is self-initiated. Cooperation could not possibly be a better choice for jobs that require data to be delivered promptly and without any delay because the growth of cooperation between users could cause delays. The combination of game theory with the MCS paradigm was one potential tactic for increasing the effectiveness of the data collection campaign. The fact that some old barriers still remain is a big obstacle to widespread recruitment. In order to motivate users to continue engaging in the system, they must be made aware of the importance of the data they gave. Xiaoyu Zhu et al. [19] presented a deep learning-based mobile vehicle (DLMV) strategy to gather sensory data in the urban environment. To forecast vehicle mobility in the future, a deep learning-based offline system was initially presented, a greedy online approach to select a small number of vehicles for the NP-Complete issue was proposed. On a shoestring budget, the algorithm generated high-quality mobile crowdsensing using vehicle trajectories. A vehicle trajectory could be obtained by using mobility prediction. The main objective was to find people in order to increase coverage while keeping costs down. An effective data collection method using mobile vehicles based on deep learning (DLMV) was presented to address the vehicle-based crowdsensing problem in the urban IoT context in order to optimise the sensed data on a limited budget. Arsham Farshad et al. [3] focused on the WiFi interface on smartphones and mobile crowdsensing-based characterization of WiFi deployment in urban areas. He specifically discussed the findings of a WiFi measuring study using mobile crowdsensing that was carried out in Edinburgh with the help of volunteers using mobile phones while riding public transportation buses. He discovered that the characteristics of WiFi deployments in public areas of various indoor environments were similar to those of WiFi deployments at the city-scale. Arsham Farshad et al. [3] compared this method to wardriving to validate it, and he also demonstrated that their findings generally concurred with earlier research using different measuring techniques. Arsham Farshad et al. [3] provided a cloud-based WiFi router setup service for enhanced interference management with global awareness in urban areas as an application of mobile crowdsensing-based urban WiFi monitoring.

Kai Han et al. [7] had studied a novel price problem for economically recruiting individuals with adequate sensing capabilities. Kai Han et al. [7] had identified certain challenging submodular features of Poisson binomial distributions and presented an ironing technique to convert the non-submodular optimization problem into a submodular one. He investigated the well-known Poisson Binomial Distribution (PBD), which was closely connected to the topic, in order to solve the PPRC problem effectively. Kai Han et al. [7] proposed a novel "ironing method" that converts PPRC problems from a non-submodular optimization problem into a submodular one. Based on these results, Kai Han et al. [7] proposed several approximation algorithms to solve problems with provable performance bounds, and the experimental results have corroborated the effectiveness of the approach. A mobile crowdsensing system had taken into account the sensing capabilities of smartphone users. Boya Song et al. [13] calculated the users' sensing quality and maintained a historical record. With a small budget, it sought to maximise the value of the activities completed. The crowd aspect was introduced by Boya Song et al. [13], who also created ABSee, an auction-based budget-feasible process that chooses winners and establishes their compensation. It was demonstrated that ABSee satisfied computational efficiency, veracity, and individual rationality in addition to budget viability. The outcomes of the simulation demonstrated that it was possible to evaluate the users' sensing quality with accuracy. Furthermore, when using ABSee instead of GREEDY-SM and RANDOM-SM, the platform could command a better price.

Bin Guo et al. [6] confronted new difficulties in platform-oriented job allocation where extra system-level factors needed to be taken into account. Bin Guo et al. [6] presented a paradigm for task allocation in multitask MCS systems in order to meet these additional issues. Most MCS jobs were location-dependent, requiring chosen workers to go to the predetermined locations in order to execute them. He suggested ActiveCrowd, a framework for assigning many tasks in MCS. He focused on the issue of worker selection in two scenarios: worker selection based on employees' deliberate movement for time-sensitive activities and unconscious movement for delay-tolerant tasks. Bin Guo et al. [6] formulated these two issues mathematically and offered two greedy augmented GA algorithms to solve them. He Li et al. [9] described a long-term incentive system that rewards mobile users that participate in mobile crowdsensing, including data gathering and forwarding, with cellular network traffic. He Li et al. [9] talked about related research on software-defined wireless networks and mobile crowd sensing. He outlined SDON's structure as well as its incentive system for mobile crowdsensing. He suggested the SDON scheme to enhance mobile crowd sensing management. Yifeng Zheng et al. [18] provided a brand-new system architecture for mobile crowdsensing that enabled encrypted truth-finding. Yifeng Zheng et al. [18] had a security design based on the confidence-aware truth discovery (CATD) method because of its cutting-edge accuracy in general and realistic mobile crowdsensing contexts with varied levels of user participation. Users uploaded sensory data that had been encrypted to the cloud, where CATD was then carried out in the encrypted space. The decryption key for the final encrypted inferred truths was supplied to the requester. The sensory information and user reliability levels, as well as the requester's implied truths, were kept secret during the entire workflow. Numerous tests using actual crowdsensing data from mobile devices resulted in usable performance on mobile platforms.

In order to ensure data privacy while evaluating data reliability, Bowen Zhao et al. [17] put forth a zero-knowledge model of data reliability estimate. The difference between dependable data and the actual data is then used to quantify data quality. Bowen Zhao et al. [17] provided participants in the task with money in accordance with the calibre of their data. He assessed PACE using a real-world dataset to show its efficacy and efficiency. The assessment and analysis findings demonstrated that PACE may stop task participants' and a task requester's destructive activities and achieve both privacy preservation and task participant data quality measurement. The suggested PACE could stop dishonest task requesters from conducting Denial of Payment attacks and unreliable task participants from launching data pollution attacks, Sybil attacks, and replacement attacks. Mingjun Xiao et al. [15] focused on the privacy-preserving user recruitment problem in sensing-quality-aware mobile crowdsensing systems. A secure user recruitment protocol, called SUR, for sensing-quality-aware mobile crowdsensing systems has been proposed. SUR adopts a greedy strategy based on a utility function to recruit users and uses secret sharing schemes to protect users' privacy. It could be proved that SUR could produce a solution with a logarithmic approximation ratio, and it could protect the inputs of each user from being revealed to the platform or to other users, even if they might collude. The simulation results have shown that SUR can work well on real smartphones when implemented optimally. Jianbing Ni et al. [11] presented a robust credit-based mobile crowdsensing system to support the protection of mobile users' privacy and task distribution for consumers. The service provider was permitted to choose mobile users based on their credit points, and the sensing areas of the activities were assigned, as well as the sensing reports that would be used for those tasks. For mobile users and customers during task allocation and report selection, sensitive information including identities, locations, credit points, sensing tasks, and sensing reports were preserved. The suggested plan

Author, year	Key contributions	P1(Internet of Things)	P2(Sensing cost)	P3(Secure data integrity)	P4(Secure user recruitment)	P5(Task allocation)	P6(Sparse mobile crowdsensing)	P7(Data quality)	P8 (Encryption)
Raghu K. Ganti et al. [1], 2012	identified a category of IoT applications that rely on data collection from large number of mobile sensing devices such as smartphones.	Yes	Yes	Yes	No	No	No	Yes	No
Leye Wang et al. [2], 2017	a sparse mobile crowdsensing prototype for temperature and traffic monitoring is implemented and evaluated.	No	Yes	No	Yes*	Yes	Yes	Yes	No
Venkat Surya Dasari et al. [3], 2020	combination of Game theory with the MCS paradigm represents a promising approach for increasing the effectiveness of the data collection campaign.	Yes	Yes	No	Yes	No	No	Yes	No
Xiaoyu Zhu et al. [4], 2020	Directly using each vehicle's trajectory to maximize the received sensing data by recruiting mobile vehicles with a limited budget.	No	No	No	Yes	Yes	No	No	No
Shihong Zou et al. [5], 2019	anonymity of the blockchain ensures that the user's identity privacy is not compromised.	Yes	Yes	Yes	No	No	No	Yes	Yes
Kai Han et al. [6], 2018	an appropriate posted price to recruit a group of participants with reasonable sensing qualities for robust crowdsensing, while the total expected payment is minimized.	No	Yes	No	Yes	No	No	Yes	No
Wei Gong et al. [7], 2018	Many task assignment mechanisms have been designed for different scenarios to achieve improved task quality or reduced task cost.	No	Yes	No	No	Yes	Yes	No	No
Jiejun Hu et al. [8], 2020	A blockchain-based MCS can achieve participant identity anonymization, decentralized reward allocation, and transparent transactions without an ordinary trusted third party.	Yes	Yes	Yes	No	Yes	Yes*	Yes	Yes
Jinbo Xiong et al. [9], 2019	Theoretical analysis and ample simulations with real trajectory dataset indicate that PERIO is effective and makes a reasonable balance between retaining high QoCS and privacy.	Yes	No	Yes	No	No	Yes	No	Yes
Bin Guo et al. [10], 2016	proposed algorithms outperform baseline methods under different experiment settings.	No	No	Yes	Yes	Yes	No	No	No
Arsham Farshad et al. [11], 2014	the characteristics of WiFi deployments at city-scale are like that of WiFi deployments in public spaces of different indoor environments.	Yes	No	No	No	No	No	Yes	No
Sumudu Hasala Marakkalage et al. [12], 2018	identified the travel patterns at several points of interest (POI), the impact of travel frequency for certain POI, and three main user profiles.	No	No	No	Yes*	No	No	No	No
Bowen Zhao et al. [13], 2019	PACE satisfied completeness, soundness, and zero-knowledge as well as achieved payment rationality and budget feasibility.	Yes*	No	Yes	Yes	No	No	Yes	Yes
He Li et al. [14], 2017	From the extensive simulation results, our incentive mechanism performs better than original solutions	No	Yes	No	No	No	No	Yes	No
Boya Song et al. [15], 2016	ABSee satisfies computational efficiency, truthfulness, and individual rationality.	No	Yes	No	No	No	No	Yes	No
Yifeng Zheng et al. [16], 2018	new system architecture enabling encrypted CATD in mobile crowdsensing to securely extract truthful information from unreliable sensory data.	No	Yes	Yes	No	No	No	No	Yes
Mingjun Xiao et al. [17], 2017	a solution with a logarithmic approximation ratio, and it can protect the inputs of each user from being revealed to the platform or to other users	No	No	No	Yes	Yes	No	No	Yes
José M. Cecilia et al. [18], 2020	MCS tools can become a powerful solution to provide smart quarantine strategies.	No	No	No	No	No	No	No	No
Jianbing Ni et al. [19], 2018	Effective and efficient Computational Overhead, Communication Overhead , Credit Analysis	No	Yes	No	Yes	Yes	No	Yes	Yes
Lei Shu et al. [20], 2018	MCS can provide a flexible, scalable, and cost-effective method for industrial sensing	Yes	Yes	No	No	No	No	No	No

placed a strong emphasis on efficiency and security. It enabled service providers to create reliable mobile crowdsensing solutions that supported precise task distribution and customer trust management. This strategy aimed to create a mobile crowdsensing framework for context-aware job allocation that protected privacy and allowed for additional resource optimization.

3 Methodology

3.1 Background

3.1.1 Definition

Crowdsensing, also known as mobile crowdsensing, is a technique that entails a sizable number of people sharing data and extracting information from mobile devices that can sense and compute (such as smartphones, tablet computers, and wearables) to measure, map, analyse, estimate, or infer (predict) any processes of mutual interest. This essentially means that sensor data from mobile devices is being crowdsourced. Using devices with sensing and processing capabilities, a community can measure and map phenomena of interest by sharing data and extracting information from them. This approach is known as mobile crowdsensing. As a result, it is also known as communal sensing. Community sensing applications concentrate on monitoring broad-scale phenomena that are difficult to measure by a single user or device, in contrast to personal sensing, where the phenomena that are monitored belong to a single user.

3.1.2 Types of Mobile Crowdsensing

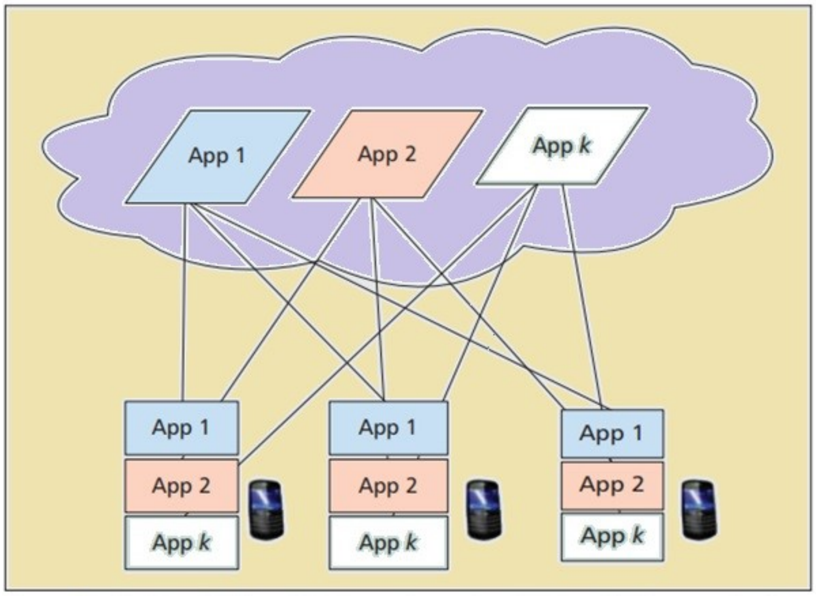
Based on the kinds of phenomena being observed, these applications can be generally divided into two categories: personal and communal sensing. In personal sensing applications, the phenomena are specific to an individual, as in the monitoring of a person's activity patterns (such as running, walking, or exercising) for record-keeping or medical purposes. Monitoring a person's modes of transportation to calculate their carbon footprint is another instance of personal sensing. Participatory crowdsensing is a method in which people willingly contribute information.

Community sensing, on the other hand, relates to the observation of widespread events that are difficult for a single person to measure. For instance, monitoring air pollution levels and traffic congestion may be necessary for intelligent transportation systems. Only when many people give speed and air quality data from their everyday travels, which are then aggregated spatio-temporally to establish congestion and pollution levels in cities, can these phenomena be assessed effectively. Popular names for community sensing include participatory sensing and opportunistic sensing. Opportunistic crowdsensing, where information is automatically felt, gathered, and disseminated without user input and, in certain situations, even without the user's express knowledge.

3.1.3 Working Mechanism

A typical MCS application comprises two application-specific components: one on the device (for sensor data propagation and collecting) and the second on the backend (or cloud) for sensor data analysis and MCS application driving. Because each application is independent of the others and is created from the ground up, we refer to this as application silos. Even while each application has a variety of similar difficulties with data collection, resource allocation, and energy conservation, there is no common component. The creation and implementation of MCS applications are hampered by such an architecture in a number of ways. First, programming an application is challenging. The developer must constantly reinvent the wheel in order to design new applications, which present energy, privacy, and data quality concerns. Additionally, if he wants to run the programme on a variety of heterogeneous devices running various OSes, he might need to create many local analytics variations. Second, this strategy is ineffective. Applications that independently conduct sensing and processing tasks without considering the effects on one another will operate inefficiently on a platform with limited resources. Duplication of sensing and processing across several applications is highly likely.

Figure 1: Existing MCS applications take an “application silo” approach where each application is built from scratch without any common component even though they face many common challenges.

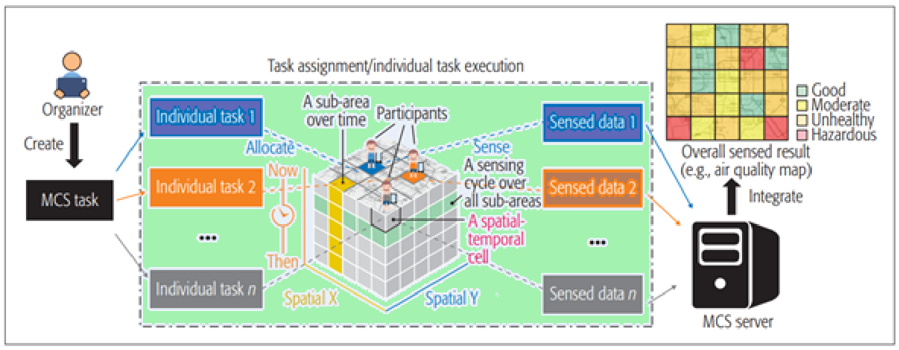


3.1.4 Diagrammatic Explanation of the working

This basic MCS Task Procedure is shown in Figure 1. Assume that the MCS task involves monitoring the air quality in urban areas. An MCS organiser first creates the MCS task (e.g., a city government or non-governmental organization). The MCS task is then divided into a number of separate tasks that can be distributed among MCS participants. Each unique task for air monitoring refers to the activity of sensing the quality of the air in a particular sub-area during a particular time cycle. Sparse MCS explicitly incorporates data inference into the MCS process as opposed to typical MCS systems that just use sparsely sensed data to assure good coverage ratios. The main difficulties in Sparse MCS will be outlined and addressed in this paper. In order to do this, we put out a generic framework for Sparse MCS applications, develop a prototype to confirm its viability, and elaborate on additional research potential. We anticipate that following the completion of this work, additional research efforts in the Sparse MCS domain may be made. This generic MCS procedure is also followed by the MCS framework known as sparse MCS, whose properties are as follows:

Sparse MCS introduces missing data inference into the server-side data integration process, which tries to estimate the missing data of unsensed cells based on the sensed data and spatio-temporal correlations between the cells. In order to achieve satisfactory data quality, Sparse MCS allocates individual tasks to only a small subset of the spatio-temporal cells.

Figure 2: Overview of the mobile crowdsensing process. A cube is used to illustrate the complete set of all possible individual tasks, where each individual task is specified by a spatio-temporal cell (a specific sub-area in a specific cycle). Two dimensions (X and Y) of the cube represent the spatial space (sub-areas), and the other dimension (Z) represents the temporal space (cycles).

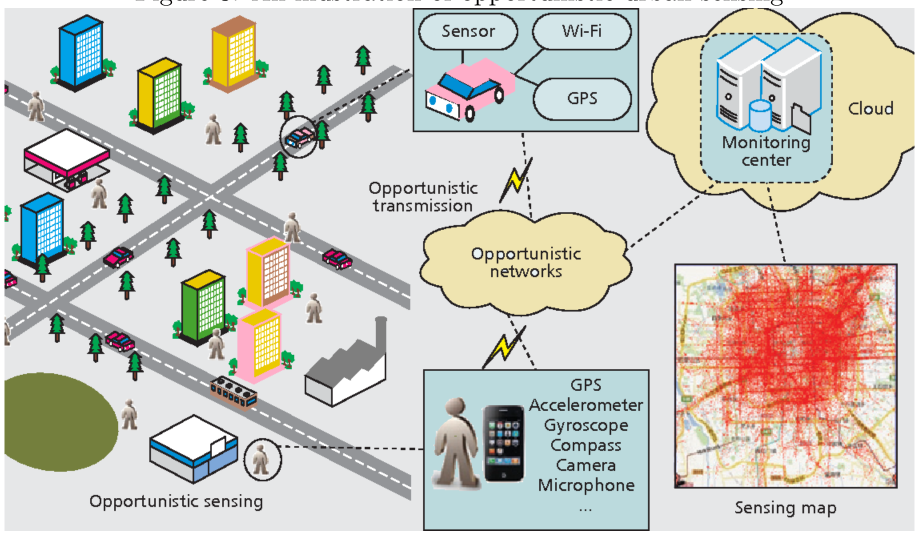


3.2 Problem Statement

A new sensing paradigm based on the strength of user-companioned devices is presented by mobile crowdsensing (MCS). The information can be further aggregated in the cloud for large-scale sensing, enabling ”the growing number of smartphone users to share local knowledge gathered by their sensor-enhanced devices.” 4 Large-scale mobile users’ mobility makes MCS a flexible platform that can frequently take the role of static sensing infrastructures. Thus, a wide range of applications are made possible, such as urban management, environment monitoring, and traffic planning. MCS has risen to prominence as a research issue in China over the past ten years. This new sensory paradigm is the result of various factors: widely used innovative methods. It has been estimated that by 2020, China will have 800 million smartphone users who utilise sensor-rich devices, making it the country with the biggest proportion of ”mobile” people in the world. This is due to the rapid improvement of mobile communication (4G/5G) and pervasive sensing techniques. In China, the proliferation of mobile devices creates a strong physical base for crowdsensing. National research and development plans’ promotion. Through several large programmes funded by its national R and D plans, China has made significant contributions to enhancing MCS. These plans encompass several significant methodologies and application domains, including the Internet of Things (IoT), smart cities, and the next stage of AI (AI 2.013). specific opportunities and challenges for development. China is becoming significantly more urbanised as a growing nation. There are many intricate problems that need to be solved, such preserving the environment, improving transportation, and managing cities. The introduction of MCS creates fresh possibilities for tackling these difficulties.

The most important part of research in the MCS is the incentive system. The sensory data may be acquired by a task initiator, who may then set a

Figure 3: An illustration of opportunistic urban sensing



price for it in the MCS framework's sensory data market. Market regulations should be followed in a sensory data market. Consequently, implementing a basic economic strategy is required. Many researchers have worked on the issue of optimal price determination and have proposed solutions [3, 6, 8, 13, 15] for the issue.

PACE aims to achieve the privacy protection of sensing data, location privacy protection, and task participant anonymity. Sensing Data Privacy Preservation specifically states that only the paying TR and data owner are permitted to access the content of the sensing data. Location Privacy Preservation means that the SP is not made aware of the TPs' locations. The term "anonymity of Task Participants" refers to the fact that no information about a TP's identity is revealed. Some researchers [5, 9, 16, 19] have touched upon the following issue.

A detailed study on the different tech for mobile crowdsensing was conducted and presented in Table 1 (survey table). Upon analysing, it is understood that more researchers [2, 5, 8, 13, 19] have worked and developed solutions on parameter 2, 4, and 7 and still, a lot of work needs to be done w.r.t parameter 5, 6, and 8 as per Table 1. Though individual mechanisms have been proposed by multiple authors the possibility of a hybrid mechanism was not explored and it is one area where authors could explore soon.

3.2.1 Discussion of Existing solutions

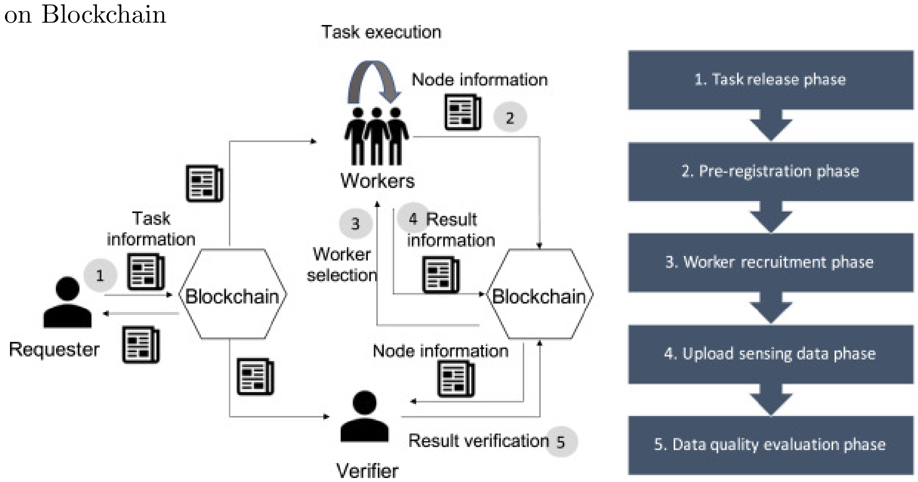
Anonymization is insufficient to protect privacy because mobile users' movements and social connections can be tracked. Based on a huge set of call data records provided by a US countrywide cell operator, it is possible to identify 35 percent of mobile users using their top-two locations and 85 percent of them using their top-three locations in a unique manner. While location privacy is one of the main concerns for mobile users in pervasive environments, geography-based task allocation schemes can optimise user selection based on their spatial and temporal correlation. However, they reveal the contents of sensing tasks and the locations of mobile users to the service provider. To preserve anonymity while completing a crowdsensing activity, CrowdBLPS uses pseudonymous Bitcoin-like addresses to identify task requesters and employees. Furthermore, we proposed the location privacy-preserving approach based on spatial cloaked areas to replace the worker's true location with a corresponding cloaked region for accepting task information, preventing the true locations of workers from being exposed to the public. This was done in accordance with the submitted working information, particularly the location information. CrowdBLPS can therefore offer a double layer of protection for both identity and location privacy.

3.3 Future Directions

A full location ecosystem, comprising hardware, firmware, algorithms, smartphone apps, and cloud servers, for future mobile smart life applications. putting out the Guoguo multi-modal step-by-step navigation eco-system, which helps the blind and visually impaired live independent and respectable lives when navigating inside environments. The prototype eco-system makes use of a variety of hardware and software elements to close the long-standing indoor localization gap. We concentrate on the implementation of context-aware information access while also emphasising the infrastructure-based fine-grained approach. Three applications for mobile smart living are proposed, including helping the blind or other disabled live independently through step-by-step navigation, automatically accessing the information through context awareness, and finding lost children or other group members through mobile crowd sensing.

In blockchain-based mobile crowdsensing, real-time data reporting is maintained on a public blockchain where every user's or node's address is visible. The issue now is that if their addresses are given to adversaries, their entire history of transactions will also be made public. Therefore, crowdsensing requires a modest privacy preservation technique that prevents the disclosure of a user's identity to an adversary. Or, to put it another way, crowd sensors must grant crowdsensing users and nodes some degree of anonymity while reporting real-time data. A single point of failure and the centralised structure of the present crowdsensing architecture make it insecure. Adversaries can also use a variety of attacks, including linking attacks, Sybil attacks, and DDOS assaults, to learn the identities of the nodes and other crucial information. Another danger that could result in hostile attacks is the position of the crowd sensors. In order to achieve privacy on the blockchain ledger, several models built on the blockchain must be proposed. Smart contracts may be the solution to this issue, allowing us to protect users from various attacks carried out by adversaries on the blockchain. The issue can be solved by establishing a crowdsensing environment on a private blockchain.

Figure 4: Overview of the architecture of Mobile Crowdsensing based entirely on Blockchain



The user recruiting procedure must safeguard against each user's sensing quality information being disclosed to other users or to the platform in order to allay users' concerns about privacy disclosures. We demonstrate that this issue is NP-hard. We first provide a Basic User Recruitment (BUR) protocol based on a greedy technique to address this issue. This protocol may effectively recruit almost the bare minimum of users while ensuring that the overall sensing quality of each work is higher than a predetermined level. We additionally provide a Secure User Recruitment (SUR) protocol based on BUR by utilising confidential sharing mechanisms. We examine the approximate ratio and demonstrate the SUR protocol's security in the semihonest scenario. Moreover, we extend SUR to deal with a more general case where the total sensing quality of each task might be an increasing submodular function.

4 Implementation

5 Results

6 Conclusion and future works

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