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SURVEY PAPER

A survey of mobile crowdsensing and crowdsourcing strategies for smart mobile device users

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Abstract
Smart handheld devices such as smartphones are capable of sensing and interacting with surrounding environments. This emerging capability of smartphones has resulted in the utilization of it as input devices and led it to be used as the default physical interface in applications of ubiquitous computing. Mobile crowdsensing is a new paradigm, which utilizes the different sensors in the smart devices to sense data from the surroundings and then transmit large amount of data to the cloud to be analyzed, managed, and stored. Crowdsourcing, on the other hand, can be defined as a model to solve a complex problem that is distributed in nature, where a crowd of unspecific size is utilized through an open call. The usage of smart devices with unique multi-sensing proficiency and context-aware capability will be able to utilize the full potential of crowdsourcing. Hence, the smart devices with the capability of sensing the environment and utilization of the wisdom of the crowd can be utilized for various benefits of the society for a better standard of living. In this survey, we present a comprehensive understanding of mobile crowdsensing and mobile crowdsourcing and how it has helped in improving the standard of living of people, specifically in the context of smart cities. Pertaining challenges have been highlighted which were creating hindrances in smooth implementation of these techniques and a few of the solutions have been discussed.

Keywords Smartphones · Mobile crowdsensing · Mobile crowdsourcing · Energy efficiency · Incentive disbursement · Device security

1 Introduction

With over one-third of the world population owning a smartphone and two-thirds of the world owning a mobile device[1], most of the world is connected to each other through the use of smart devices. In the coming years, the usage of smart handheld devices are expected to rise at a rapid rate that will ultimately lead to all the world population utilising one of these mobile devices. All the mobile devices are potential sensing devices and play a crucial role in exploring new class of intelligent networks in our surroundings which are interconnecting the Internet of Things (IoT). This has in turn resulted in amalgamation of cyber and real life physical objects in our day to day life.

Mobile Crowdsensing (MCS) (Liu et al. 2016) refers to the wide variety of sensing models by which individuals collectively share data and extract information to measure and map phenomena of common interest. These systems heavily depend on the rich set of sensors and communication modules that are firmly affixed in the smart devices like smart phones and wearable gadgets (Ganti et al. 2011). These sensors are used to sense the surroundings, collect the data that is being sensed and then send the data to the server which may be present in cloud or to some other smart devices for further processing of the data.

In recent times, to understand the capacity of the MCS to full extent various types of application have been introduced in everyday life. The different types of mobile crowdsensing applications are environmental monitoring (Zhang et al. 2014), traffic managements (Mohan et al. 2008), urban sensing, social networking services, health care, and public safety to name a few. The sensors in the smart devices continuously sense the environment, so a huge amount of raw data is being produced which in turn results in utilization of

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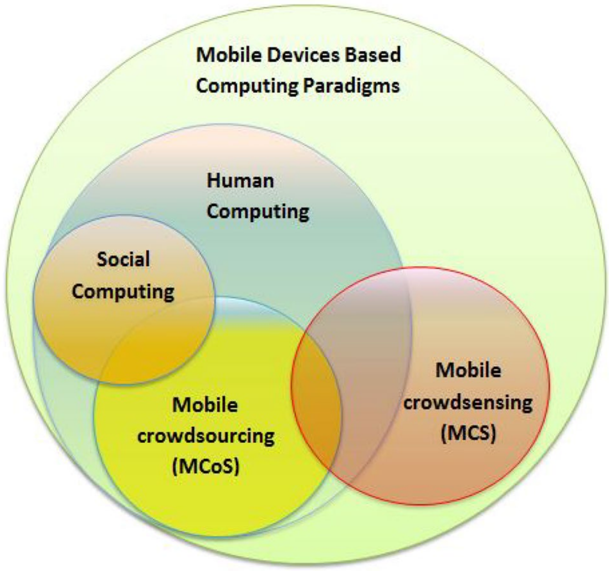

Fig. 1 Computing paradigms that emerged based on the wide usage of smart devices

the limited resources of the smart devices (Liu et al. 2015). This may also lead to compromise in the quality of data sensed. Hence the limitations of the resources pose a major problem in the mobile crowdsensing Hua et al. (2015)- Shen and Li (2014). Inspite of being a new paradigm, MCS has been utilized in real life applications (Chon et al. 2012), (Mohan et al. 2008). The application domain of MCS systems includes both academic as well industrial sectors, with a stress on maintaining cost-effectiveness and quality of service.

1.1 Motivation

Figure 1 highlights the computing paradigms that emerged based on the wide range of smart devices. The four paradigms covered are:

1. Human Computing - It refers to the process of outsourcing human intelligence for computational services provided by the crowd and at times engaging human reasoning in case of context aware data collection. Participation of human computing is much higher than other paradigms. In Pantic et al. (2007), authors provide a survey on the progress of human computing in achieving an environment for an elevated user experience.
2. Social Computing - It is the recreation of social behaviour through the use of software and technology, such as blogs, social networks, wikis and so on. Social computing can be traced back to the early days of online gaming and predecessors of social networks, to augmented reality and other three dimensional virtual reality and a great prospect of growth (Messinger et al. 2009).
3. Mobile Crowdsensing - Crowdsensing is the participation of crowd with smart mobile devices to collect, compute, and analyze data. In Liu et al. (2019), a comprehensive survey of MCS technologies is provided with focus on data. Quality control is the main focus of the survey presented in Restuccia et al. (2017). In Capponi et al. (2019), authors have discussed an extensive taxonomy of research work related to MCS in recent years.
4. Mobile Crowdsourcing (MCoS) - Crowdsourcing is the process of obtaining services from a large, open and evolving group of participatory crowd. In Feng et al. (2017), authors presented a survey of crowdsourcing models with an emphasis on privacy. The work in Kong et al. (2019) provides a survey on MCoS with respect to smart cities and smart city based applications.

The existing survey works are found to deal with each of these four paradigms mainly focusing on one or more challenges associated with each of them. However, MCS and MCoS paradigms are related to each other sharing a few similar sets of challenges that are handled either similarly or separately in the existing literature. Thus, the aim of this survey is to emphasize on Mobile Crowdsourcing and Mobile Crowdsensing paradigms. An extensive survey on the architecture and implementation of different models of MCoS and MCS not only highlighting the hurdles but commenting on the possible solutions is missing in the current literature. An extensive taxonomy from multiple perspectives emphasising the need and current classes of MCoS and MCS is also not present in relevant research documentation. Thus, the motivation of this survey is to cover the participatory behaviour, architectures, taxonomies, and potential research directions of MCS and MCoS extensively and largely exhaustively.

1.2 Objective

This survey is structured with the following objectives:

- compare and contrast the different mobile crowdsourcing and mobile crowdsensing models.
- highlight the benefits and limitations of existing mobile crowdsourcing and mobile crowdsensing models.
- bring to light the future directions of research in MCS and MCoS.

The remainder of the paper is structured as follows: Sect. 2 discusses the background of the MCS and MCoS. Section 3 describes the architecture of MCS and MCoS. Section 4 discusses the numerous challenges faced while implementing MCS and MCoS in different applications and the various solutions are also discussed. Section 5 discusses the existing

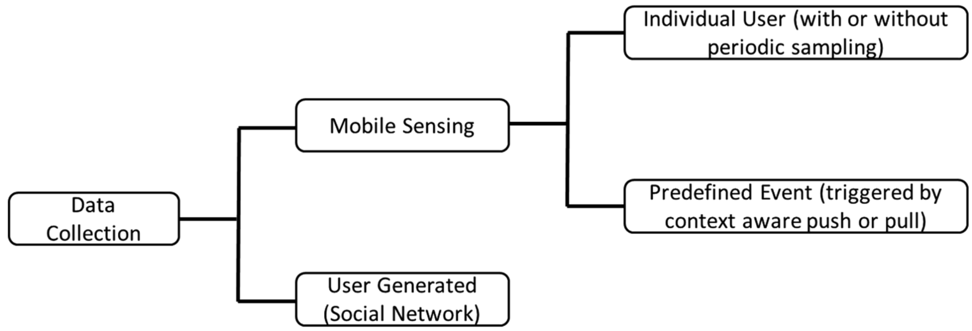

Fig. 2 Different Modes of Data Collection Mechanisms for Mobile Crowd-sensing Applications

mobile crowdsensing and mobile crowdsourcing strategies. Section 6 discusses the subsequent direction in which the researches need to be done in future for better implementation of MCS and MCoS while Sect. 7 concludes the paper.

2 Backgrounds

In this section, we introduce the main concepts of the mobile crowdsensing and mobile crowdsourcing.

2.1 Mobile crowdsensing

For large scale sensing and environmental monitoring, a huge number of participants are required to sense the raw data from the surrounding, with the help of sensors that are embedded in the smart devices of the crowd. Based on the type of phenomenon being measured or mapped, MCS applications can be divided into three categories: (a) environmental applications, (b) infrastructure applications, and (c) social applications (Ganti et al. 2011). The three essential steps for mobile crowdsensing includes: data collection, data storage and data upload. The very first step in MCS is data collection (Lane et al. 2013) which is broadly divided into following categories as in Fig. 2:

- In the first category, it is done through the sensors of the mobile device. Here, individual user's mobile device may sense data with users permission and also sensing data through periodic sampling, or user is solely responsible for collection of the sensing data by his mobile device. Also the collection of context-aware data can be activated by certain context that is predefined (e.g., certain location or time slot). The user is not responsible for continuously keeping her/his attention to MCS jobs.
- In the second category (Guo et al. 2014), a large amount of data is collected through mobile social network.

Context-aware sensing (Pietschmann et al. 2008) can be achieved by two ways: push and pull. In case of push based data collection, the sensing device periodically or instantly sends data to the software module which is responsible for obtaining the sensed data. It enables to issue or endorse a model periodically. On the other hand, in case of pull based data collection, the software module is responsible for obtaining the data that is being sensed, periodically or instantly by making a request to the sensors of the smart devices.

There is often redundancy or duplication of the data that is being sensed.As redundancy leads to wastage of the limited resources of the smart devices, it hinders the MCS implementation. Data deduplication is a procedure that aid in reducing the resource consumption but at the same time improves the QoS of the data that is being sent over the network. In this procedure, the raw data that is being sensed goes through a process of filtering and compression at the same time maintaining the quality of the data (Liu et al. 2016), (Barik et al. 2021). In this way the usage of bandwidth is reduced while transferring the data as well as less space is used to store the data. In this method, the data obtained after sensing is first divided into blocks, and only the unique blocks are stored. All other incoming blocks are compared with the unique block, if superfluous blocks are encountered then it is replaced by a reference (Puzio et al. 2014), (Ebinazer et al. 2021). Only the unique block and the references are transferred over the network. This way, it helps in reduction in size of the data that is transmitted, and bandwidth consumption.

Based on the phase of occurrence of deduplication, it can be classified into two types as can be seen from Fig. 3,

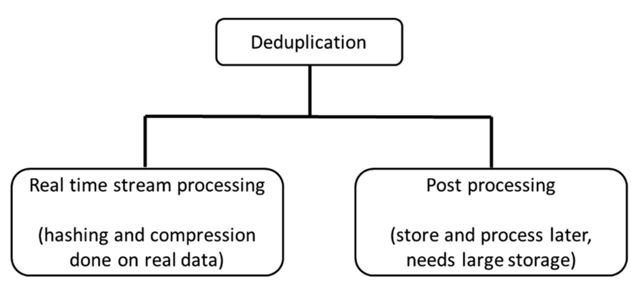

Fig. 3 Types of data deduplication based on phase of occurrence

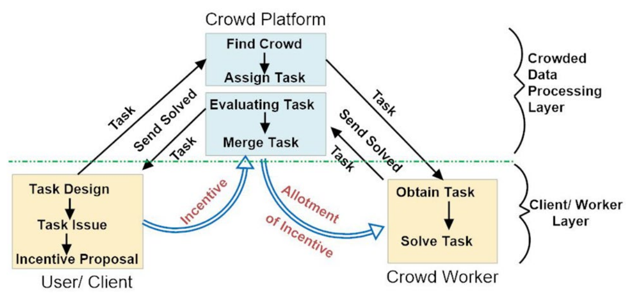

Fig. 4 Illustration of working of MCoS

real time deduplication (Kim et al. 2016), (Wildani et al. 2013), (Srinivasan et al. 2012) and post-process deduplication (Yang et al. 2010), (Meyer and Bolosky 2012), (Kathpal et al. 2011). In case of real-time deduplication, at the time of acquiring the data, hashing and compression is done on the raw data. When fresh set of data is being obtained, it is compared with the stored data in the smart devices. If the data is found to be redundant then it is discarded. Though the storage space gets reduced, the computational load moves from the crowded data processing platform to the terminal i.e., the mobile device. Hence, it would be a practical problem in situations where the devices have very limited computational capability. In case of post-process deduplication, the data after sensing is stored in the local mobile device and then further processing takes place on the sensed data and thus reduce the real-time computational issues. In this method, the device needs to have a bigger storage space for storing the huge set of raw data for processing else there is a risk of overwriting of the stored data when the storage space is less.

2.2 Mobile crowdsourcing

Mobile crowdsourcing enables in dispensing off a complex workload to a suitable group of Internet users who are interested in participating to solve a task (Phuttharak and Loke 2019), (Wang et al. 2019), (Wang et al. 2021). This can be achieved by utilising the mobile distributed computing and the use of human logical mind where computers fails to decipher a problem. Different users may offer different solutions to solve a particular problem. Fig.4 explains how a task is assigned to the crowd worker by the client, how the task is being solved and how the workers are paid incentives for completion of the task summarizing the works in Chen et al. (2021). Sometimes a task is divided into sub-tasks and those subtasks are given to the crowd to solve individually. These subtasks are then sent by the crowd to the crowdsourcing platform where the subtasks are merged to form a feasible solution. This solution is then forwarded to the end user. Crowdsourcing (Zheng et al. 2014) helps in performing a task faster than an individual, helps in better quality of results and the results thus obtained are more acceptable as it is supported by a large population of people participating in solving the tasks. For e.g., the work in [28] can be used to provide solutions for retail auditing using MCoS. The pitfalls of an in-store can be very well explained if an auditing is performed based on customers feedback of the store. MCoS helps in getting the information regarding customers experience, stock levels of the store, display compliance all in real time. This crowdsourced data will help in making important decision for the retail store. Due to the availability of a large number of real time smartphone-enabled shoppers nationwide, it is very easy to obtain data such as photos of the product, get replies to queries based on sentiments of the shoppers and so on. Near real-time data is another factor which helps in predicting the ever changing nature of the retails. To be on top and in trend, up-to-date data is most necessary. To make important business decision a set of high quality of data is required. MCoS platform ensures that there is certain level of standards of the data that is being provided by the crowd. Hence the MCoS works well for this case as a large variety of replies can be obtained from the customer in real time in aiding to decision making process with the implementation of the up-to-date changes necessary.

Following are few such benefits of utilizing crowdsourcing for accomplishing a job.

– Reduces cost as instead of paying the professional testers in hourly basis, the company reimburse only for the bugs that are being found. Here huge number of participation results in finding more reproducible bugs than few testers.
– Crowd participation results in a diverse high-quality data that is continually and actively upgraded.
– Due to the availability of different sorts of parameters, crowdsourcing helps in a more thorough and extensive testing.
– Time efficiency due to the multiplicative effort of the crowd.

The outcome of the crowdsourced data may be more acceptable due to representative involvement of the crowd. The application of MCoS has reached to far greater areas than it was thought of while conceptualizing. Powered by GPS, the smart devices are capable of collecting real time and location dependent data which can be implemented in various applications ranging. For e.g., helping disaster victims by synchronization of relief program and recording the damages done all in real-time, in business with its far reach and flexibility for various applicable proposals. The various application areas of MCoS includes social networking and issues (Punjabi et al. 2013), (Eilander et al. 2016), environmental monitoring and utilities (Rana

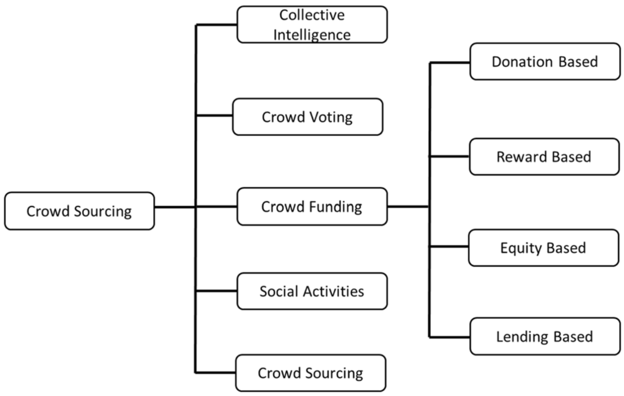

Fig. 5 Types of Crowdsourcing

et al. 2010), (Matsuyama et al. 2014), (Zhang et al. 2018), (Mccallum et al. 2018), traffic, navigation, transportation and urban sensing (Grazioli et al. 2013), (Kwak et al. 2014), (Fan et al. 2013), (Boss et al. 2018), disaster report (Wang et al. 2018), (Eilander et al. 2016), (Reilly et al. 2013), translation (Unbabel - Machine 2019), (Gimpel et al. 2011), health monitoring (Yi et al. 2012), (Pryss et al. 2015) and public safety (Ballesteros et al. 2015), (Hamilton et al. 2011).

The various types of crowdsourcing are as follows from Fig. 5

- Collective intelligence: it refers to contribution of individual's understanding with the crowd.
- Crowd voting: It depends on the judgment made by the crowd. Crowd votes in favor of the best according to crowd's intelligence. For instance, Yahoo's search produce results performed by crowd voting, as the result is outcome of the sites which are more popular among the users of the Internet.
- Crowd creation: it refers to the combining endeavors of the crowd to construct a product or service.
- Crowd funding: The main idea of crowd funding individuals asking help for a sum of money for a particular endeavor. For example, providing lunches for children in poor countries or for providing funding for startups.
- Social Activities: it refers to human inspired activity where social interaction by the crowd helps in collection of information with the help of technology.

A brief summary of the similarity and differences of MCS and MCoS has been put forward and explained in Table 1.

3 Mobile crowdsensing and mobile crowdsourcing architecture

Both MCS and MCoS paradigms grossly follow a four tier architecture where the smartphones are the end devices while the data processing is typically executed at a cloud server.

3.1 Mobile crowdsensing architecture

Mobile crowdsensing (MCS) is a four layered architecture as can be seen from Fig. 6. The bottom layer is the mobile sensing layer. The responsibility of the sensing layer is to collect the raw data sensed by the sensors of the mobile device, and then apply some privacy rules to these data. This is very important as the data that is to be shared by the mobile user may have private information which needs to be protected. This data is then transmitted by the transmission layer. This layer uses various communication technologies to transmit the data to the third layer above it. The next layer is the crowded data processing layer. The responsibility of this layer is to collect the data from various sensors, clean the data, analyse and then store the data in the backend server/cloud. The fourth or the topmost layer is the application layer where there are users who needs the services from the crowded data processing layer such as information regarding urban planning, environmental monitoring, etc. The users send request to the crowded data processing layer and then

Table 1 Summary of similarity and differences of Mobile Crowdsensing & Mobile Crowdsourcing

Area	Mobile Crowdsensing Vs Mobile Crowdsourcing
1. Data Collection	In both MCS and MCoS, data collection is through sensors in the device as well as social networks
2. Privacy & Security	In both MCS and MCoS, concerning challenges are anonymization, data security and privacy
3. Task Handling	In MCS, task is restricted to sensing of raw data, preprocessing of data by the mobile device. However, in MCoS, tasks comprise of not only sensing and preprocessing of raw data, but also certain other jobs assigned by the cloud platform
4. User Participation	Both MCS and MCoS motivate user participation for performing tasks
5. Incentive	In both MCS and MCoS, various incentive mechanisms are adopted to influence the crowd to perform tasks
6. Human Intelligence	In MCS, human intelligence is not required to perform the tasks but in MCoS often tasks are solved by combining the computing power of the mobile device and human intelligence

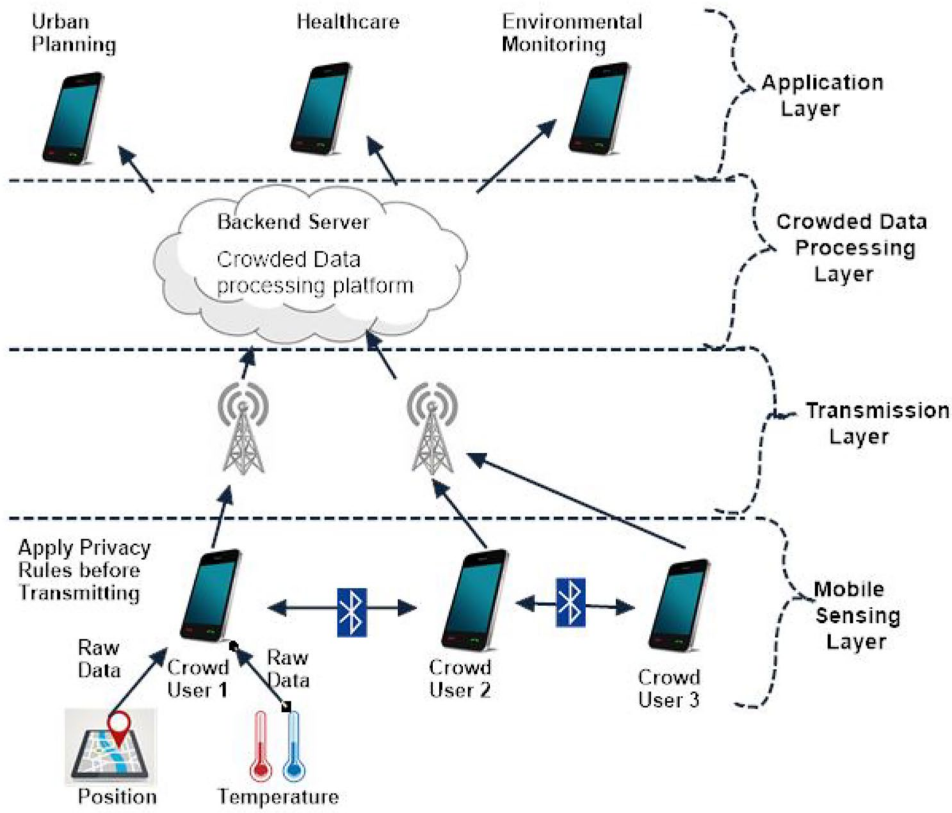

Fig. 6 Mobile crowdsensing Architecture

the query is replied back with the help of the analysed data stored in the backend server/ cloud.

3.2 Mobile crowdsourcing architecture

Mobile crowdsourcing architecture is centralised in nature. Typical MCoS application is implemented following client-server model of communication based on web technology. As can be seen from Fig. 7, the model is generally a four-tier architecture namely, (a) Mobile sensing and computing layer, (b) Transmission layer, (c) Crowded data processing layer, and (d) Application layer (Client). The top most layer is the application layer. The end user/ requester asks for a certain tasks to be completed/ solved by the mobile crowd user. Hence, it requests to the crowded data processing layer. The requester is not aware about the participants that are involved in solving the task. The next layer is the crowded data processing layer. It has various responsibilities. It takes the responsibility of accepting the tasks allotted to it by the end user, then it decides which crowd user/ users to disburse the tasks based on the record it maintains, for determining the efficient workers. It also collects the various solved tasks sent by the crowd workers and then aggregates the tasks (if needed). The aggregated tasks are sent to the requester of the tasks. This layer disburses the incentives based on the efficiency of the task performed, quality of the tasks

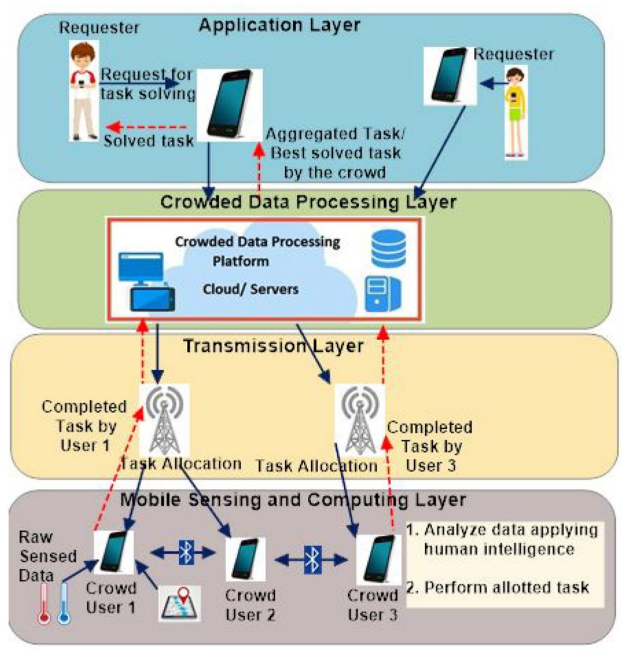

Fig. 7 Mobile Crowdsourcing Architecture

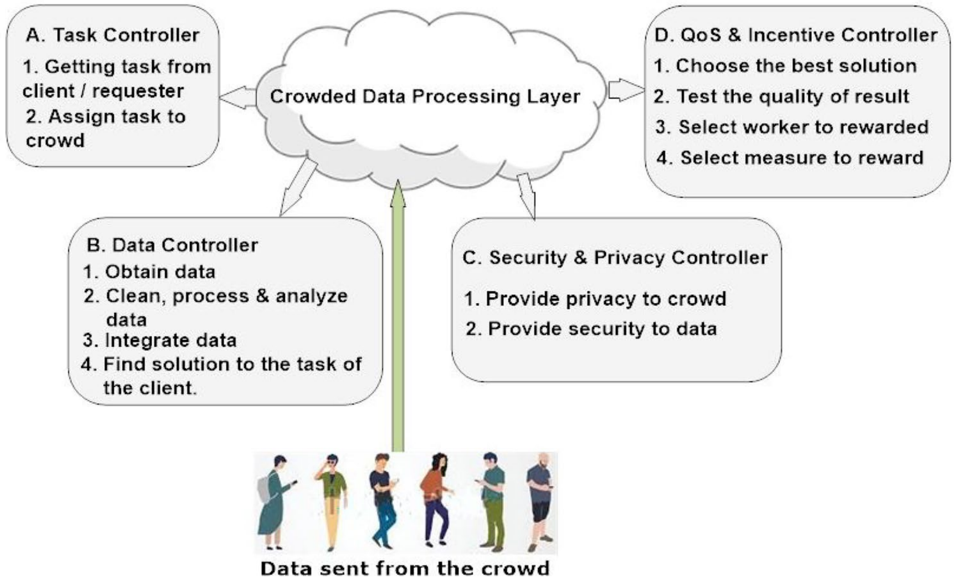

Fig. 8 Detailed view of the Crowd Data Processing Layer of the mobile crowdsourcing architecture

and so on. This layer is also responsible for data collection, processing and refinement by various methods such as filtering and then the data is compressed to be sent to the higher layer. The next layer is the transmission layer through which the tasks are disbursed to the crowd workers. The network can be heterogeneous in nature from wireless sensor network to cellular network to ad hoc networks. This layer helps in keeping the connection to all the participating devices via device discovery mechanism for location-aware data. Researches (Zhou et al. 2018), (Dighriri et al. 2018) are found to enhance the throughput of devices that have low cellular data rate. The lowest layer is the mobile crowdsening and computing layer. Here the job of the crowd is to solve a certain task. It is also responsible to sense data when needed, and processes the data with the help of the mobile device or human intelligence and then sends this processed data to the higher layer for further analysis and storage. The sensing can be done in participatory method or by opportunistic method (Ganti et al. 2011).

MCoS platform is greatly benefited by the cloud computing as it gives ample storage capacity for stocking the data, saving energy consumption of the smart devices and increasing the battery lifetime (Dinh et al. 2013). This layer consists of four controller elements for enhancing the functionality of the layer as depicted by Fig. 8. They are: (1) Task controller, (2) Data Controller, 3) QoS Controller and (4) Security and Privacy Controller.

1) Task controller: The main job is to obtain tasks from the client end and assign and distribute the tasks to the participants of the crowd. Here, importance should be given to the job of assigning the tasks. The tasks controller determines how many sub tasks the tasks need to be broken down and to whom the tasks should be allotted to get the desired results. The standard of the tasks depends on task design (Zamora et al. 2016), (An et al. 2015), hence, care should be taken about the type of tasks, the probable time taken to execute the tasks and the constraints that may be there before allotment of the tasks. In Peng et al. (2018), author suggests CrowdService, a method implemented by genetic algorithm, which can find a near optimal set of crowd participants at near optimal cost and time constraints for a given task. In Qiu et al. (2016), authors propose an approach to efficiently minimize the cost at the same time maintain the task accuracy.
2) Data controller: The main job of this module is to obtain the data from the workers of the crowd, clean the raw data, process the data, analyze the data, integrate the data and find solution to the allotted tasks submitted by the client side. Various data processing methods such as, data mining and data integration may be implemented on the data to obtain the best data set Phuttharak and Loke (2019).
3) Quality of Service and Incentive Controller: One of the functions of this module is to choose the best result. Various methods such as majority voting, control group or expert decision Hirth et al. (2013), Tu et al. (2018), Chamberlain et al. (2018), Li et al. (2018) have been proposed to obtain the best response from the participants of the crowd. Another function is to check the standards of the results. This is important as the data obtained from the crowd should be having certain level of quality. In Dow et al. (2012), the assessment of the data is categorized into three steps namely: no assessment, self-assessment and expert assessment. It

is observed that some level of assessment produces better results from the crowd. Finally, this module is also responsible for identifying the workers that needs to be rewarded. Incentive is very important as if the workers are not rewarded then they may drop out of the crowdsourcing tasks (Yang et al. 2016). Monetary incentive is very useful in motivating the crowd workers (Teodoro et al. 2014). Decision should be taken on the nature of reward that the worker would be given based on the quality of the work.

4) Security and privacy controller: The major goals are to provide privacy to the participants of the crowd without disclosing of the identity of the workers, provide security to the data that is being shared by the workers. In Geiger et al. (2011), authors have suggested that the accessibility of the peers can be in different levels namely: none, view, assess, modify. These control mechanisms provided to the crowd participants will enable the workers to take decision about what they want to do with the data i.e., managing the data or take decision in removing the data.

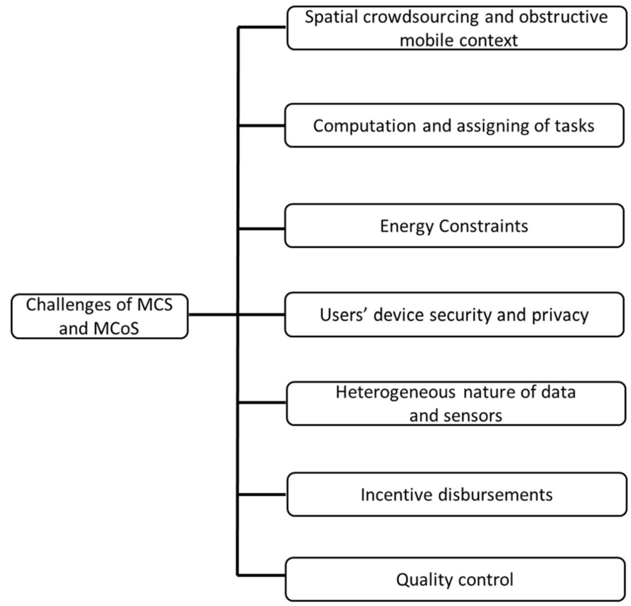

Fig. 9 Challenges of MCS and MCoS

4 Research challenges and existing approaches

Voluntary users' participation of the crowd is the basis of MCS and MCoS application. In this process the participants lend their smart devices which results in draining of the energy of the devices at the same time the participants compromise their privacy and security by sharing the sensed data which may at times have location-sensitive information attached to the data. Another issue that may arise is the mindset of the participant. The participants may be having malicious intentions or selfish or can be erroneous at times. This may create problem in obtaining high quality data. Hence, the pertinent research challenges are discussed in the following subsection. The subsequent subsection presents a discussion of the existing works that addressed these challenges.

4.1 Challenges of MCS and MCoS

The various challenges faced by MCS and MCoS systems are (Fig 9): (a) Spatial crowdsourcing and obstructive mobile context, (b) Computation and assigning of tasks, (c) Energy constraints, (d) User's device security and privacy, (e) Heterogeneous nature of data and sensors, (f) Incentive disbursements, and (g) Quality control discussed as follows.

4.1.1 Spatial crowdsourcing and obstructive mobile context

Mobile context-aware computing necessitates the device to be conscious of its surroundings (Guo et al. 2015), (Tong et al. 2017), (Zamora et al. 2016), (Chen and Kotz 2000). Context may include geographical mode, kinetic mode, temporal mode, social mode, user profile or any particular phenomenon about a situation. For allotting the correct task to the deserving participants of the crowd at the correct time and in the right circumstances, context of the participant needs to be known (Afridi 2011). Context aware MCoS not only aids in reducing the energy consumption of the mobile device but also creates situation that helps in maximizing the chances of participation of the relevant user (Tamilin et al. 2012). Spatial crowdsourcing is a very favored category of crowdsourcing also known as geo-crowdsourcing or location-aware crowdsourcing where the workers need to be physically present at a specific location at a specific time to perform the task which may comprise of collecting, analyzing and circulating the social or geographical information about the surroundings. Various researchers have talked about options of utilizing crowd to perform specific task which is at a specific location.

4.1.2 Task design and allocation of tasks

Crowdsourcer/user defines the task that needs to be done by designing the task. The crowdsourcer in order to get the task done by eligible participants may state criterion or define the procedure of assessing the task and the incentives to be given. Three important issues of task design are Allahbakhsh et al. (2013): task definition, user interface and granularity. In task definition, the crowdsourcer defines the nature of the task, time limitations, the requisite qualification needed by the workers to have. User interface defines how the crowdsourcers allocate the task to the crowd. Simple interface may be easier to work and encourage more participants but at the same time it may increase the chances of malicious worker to deceive the crowdsourcer. Complex interface though may help in authenticating the worker, it may also create unwanted complications and discourage the participation of the crowd. Granularity is a degree of the level of detail in data. For example, in time series data, the granularity of measurement might be based on intervals of data collection period. If required the granular data can be summarized or otherwise aggregated in order to do specific analysis.

4.1.3 Energy constraints

This is a growing issue in all MCoS applications. In spite of new technologies being invented to increase the battery life of the smart devices, it is still not sufficient to cater the present scenario of application. In a study (Balasubramanian et al. 2009) it is found that the energy consumed while transmitting data across WiFi is significantly less than through 3G or GSM. MCoS applications require the participation of large number of mobile users for collecting, analyzing and sharing of data which results in drainage of battery. Hence, willingness to take part in crowdsourcing depends on the amount of energy that may be consumed while doing so Ganti et al. (2011), Wang et al. (2018). This decision also depends on the current load on the device, recharging probability etc.

4.1.4 User's device security and privacy

Security in case of MCoS are critical than conventional computing methods due to Yang et al. (2015): participation of human, crowdsourcing of tasks and dynamic nature of topology. Due to the human involvement in MCoS, the private data of the participants particularly the location of the device may get compromised. The owner of the device may also have malicious intentions and can set attacks. Crowdsourcing of task can also pose a threat as the task may contain sensitive information and while crowdsourcing the task is allotted to a group of workers rather than a single worker hence, protecting the private information is more challenging. Supporting complete privacy at some points may hinder reproducibility of the results as the complete dataset is not available to the MCoS application designer. Mobility of the crowd workers can also increase the problem of providing security and privacy to the sensitive data in the device. The completed tasks that are submitted by the workers generally contain spatio-temporal-social information. In this context even if the crowd workers are given proper incentive but they may not be willing to participate in the fear of compromising with the privacy or the security of the data.

4.1.5 Heterogeneous nature of data and sensors

Data collected from smart devices (sensors in cars, drones, bicycles, traffic cameras and so on) are of heterogeneous nature. For example, traffic monitoring systems and telemetry systems generate massive amounts of spatio-temporal data in the form of geolocated time series and timestamped trajectory data (Neves et al. 2020). Preserving privacy in heterogeneous data or data from heterogeneous sensor networks is an active research challenge (Zhao et al. 2020). Recruiting workers for heterogeneous sensing tasks involving heterogeneous data is another such research challenge (Gao et al. 2020). Deduplication of massive amounts of heterogeneous data is another such research challenge (Zhang and Chen 2022).

Processing such heterogeneous data finds multiple applications, such as, better disaster management by processing multitude of sensor data received from infrastructural and human-based sensor data available (Abu-Elkheir et al. 2016). Another such application is identifying human behaviour in a smart environment based on heterogeneous data obtained from multiple sensory devices (Lupión et al. 2021). Another novel application is the use of smartphone inertial data aiding GPS trajectories and road network data for more personalised and accurate travel time estimation (Gao et al. 2022).

4.1.6 Incentive disbursements

Participants in crowdsourcing require certain incentives for sharing collected data. For example, for contact tracing data for tracking the spread of COVID19, the participants require incentives to share sensitive information (Wang et al. 2021). Retrieving large scale data through crowdsourcing can be yet another challenge, and diffusing the data collection task through social networks utilising influence-based incentive mechanisms (Xu et al. 2021) can be utilised. One of the primary focuses of incentive management techniques with respect to crowdsensing is to maintain reliability and privacy (Zhao et al. 2021). Finding willing participants in the initial cold-start stages of crowdsensing tasks through effective incentive disbursement (Lin et al. 2021) also requires special attention. Another growing field of research is to address selective fairness, bounded efficiency, and truthfulness in incentive mechanisms for multi service exchange in MCS (Lu et al. 2022).

4.1.7 Quality control

Due to the distributed nature of the crowd and anonymity, the quality of the crowd sourced data needs to be evaluated as at times there is financial involvement. It is difficult to increase the standard of quality of the crowd though the participation of the crowd members may increase because at times due to gain in monetary benefits the crowd workers may cheat the system. MCoS applications require to work with a varied type of workers each of them reveal diverse behaviors (Gadiraju et al. 2015). Hence, controlling the quality in such a scenario is a challenging task.

4.2 Approaches to solve the issues

4.2.1 Spatial crowdsourcing and obstructive mobile context

The challenge of getting enough data for spatial crowdsourcing is addressed in the literature mainly through encouraging user collaboration. In Guo et al. (2016), Du et al. (2018), Atzori et al. (2017), Hu et al. (2014) a context-aware organization model is being proposed that not only help the members of the group to collaborate with each other in mobile environment but also provide a way to find solution by weighted majority voting scheme.

In Tong et al. (2017), the authors divide the tasks into two types: static(offline) and dynamic(online). Endeavor is given to maximize assigning of tasks to the valid workers present in static scenario. In dynamic scenario, effort is given to maximize the number of pairs of dynamical workers and tasks with strict budget. Selection of workers can be based on the type of application it is implemented on. Workers can be of two types Zhao and Han (2016): reward seeking worker who gets some amount of reward in the form of commodities or money when they are able to perform certain tasks in specific time Xie et al. (2009), and voluntary worker who performs location-sensitive tasks. These participants are self-motivated to perform the tasks. In spatial crowdsourcing the workers needs to be at a specific location in specific time whereas in Web-based crowdsourcing the workers do not need to be physically present (Zhang et al. 2016).

4.2.2 Task design and allocation of tasks

Granularity defines the way the tasks can be broken down. Simple tasks are short, self-contained, take less time for completion and require little expertise. Since complex tasks take more time and expertise, hence, need to be broken down into sub tasks and allot to specific expert participants to get it done. Once all the sub tasks are completed then the complex task needs to be consolidated to get the ultimate solution. Task allocation defines how a task is to be allotted to specific eligible group of crowd who has the expertise to solve the task efficiently and accurately. In Boutsis and Kalogeraki (2013) the authors discusses about allocating of task by collaborating scheduling methods with crowdsourcing. Task assignment problem can also be solved by online primal-dual technique. The authors Ho et al. (2013) propose a near optimal adaptive assignment algorithm that helps in lowering of cost as well as giving more accurate result prediction when the availability of the workers are diverse. Social attributes of the crowd and mobility path of the mobile user is taken into consideration to decide the task allocation (He et al. 2014). Social aware task allocation scheme is adopted which is based on degree of matching between crowd workers and task, in order to decide which participants of the crowd are best suited for performing the task (Ren et al. 2015).

4.2.3 Energy constraints

So efficient energy saving techniques are being discussed to enhance the participation rate (Liu et al. 2016), (Wang et al. 2018). In Zhuang et al. (2010) the authors proposed an adaptive scheme by switching to energy-efficient but less accurate WiFi/ cellular localization from accurate but energy hungry GPS to obtain the location of the mobile device. A couple of framework (Zhang et al. 2014), (Xiong et al. 2016) are proposed for assignment of task to keep the energy consumption low by selecting the number of workers to a minimum while making sure that the quality of the tasks is not compromised. But it can be observed that the variety of sensed data and the different energy consumption level have posed a challenge for improving the quality of the data and for reducing the energy consumption.

4.2.4 User's device security and privacy

Cryptography is a mechanism by which the data can be protected from the intruder while transmitting. In Chon et al. (2012), authors propose a time window of 24 hours during this time the user can delete data that is considered too sensitive. The user can also stop sending of data if the user foresees any chances of threat. In Cornelius et al. (2008) authors propose AnonySense which provides privacy protection across multiple layers without human intervention. Hence, a user participates in crowdsourcing of data without getting the privacy compromised. Privacy of the spatial crowd worker can be maintained by masking the location information of the crowd workers which works on the differential privacy approach (Huang et al. 2017), (To et al. 2014). Another approach towards improving the security and privacy of mobile crowdsensing and mobile crowdsourcing is through the integration of blockchain Chen et al. (2021). The integration of blockchain also helps in incentive disbursements.

4.2.5 Incentive disbursements

An incentive is a form of motivation provided by crowdsourcer to crowd worker as an encouragement to perform a task. Based on decision control, incentive mechanism can be classified into two types: crowdsourcer-centric, where the crowdsourcer is the decision maker, and user-centric, where the crowd worker is the decision maker. Incentive may be economic or non-economic. Economic incentives might be direct payments or discounts offered such as reserve price (Yang et al. 2016), which is the minimum monetary amount, decided by the crowd worker, for performing a task. Monetary incentive and setting the scheduling of task also influences the participatory behaviour of the worker (Teodoro et al. 2014). It is also seen that if the return on investment is not up to the expectations then the workers may not opt to participate in the crowdsourcing (Guo et al. 2014). Non-economic incentive can be social incentive, in form of gaining reputation or public recognition and entertainment based incentive where crowd participates for enjoyment or fun activities (Liu et al. 2012). Earning reputation on successful completion of task (Zhang and van der Schaar 2012) is another non-economic incentive. Reduced distance to task location and the area's socio-economic status (Thebault Spieker et al. 2015) is yet another non-monetary incentive. Providing positive feedback and encouraging the members as a form of moral boost also helps in retention of a worker and making the worker contribute in crowdsourcing (Kraut and Resnick 2012).

4.2.6 Quality control

Without proper screening, the data submitted by participatory crowd might be erroneous or biased in nature. The introduction of error or bias in the submitted data might be intentional or unintentional. In Quinn and Bederson (2011), authors proposed various methods to control the quality in MCoS namely, incentives, task design, reputation, input agreement, output agreement, majority consensus, contributors evaluation, real-time support, workflow management, and ground truth seeding. In Allahbakhsh et al. (2013) the authors make use of the workflow management, worker selection, run-time support and contributor evaluation to control the quality of the crowd sourced data. There are multiple ways of improving not only the quality of data, participatory behaviour and incentive disbursements as well, using different game theoretic approaches Dasari et al. (2020).

5 Discussion on existing mobile crowdsensing and mobile crowdsourcing techniques

5.1 Techniques used in mobile crowdsensing

In this segment, some condition based techniques are being discussed which gives us insight of how to reduce the consumption of resources, reducing the energy that is consumed and at the same time maintaining the QoS of the data that is sensed. From Dao et al. (2014), Aggarwal et al. (2011), we come to know that the content of sensed data is often redundant due to the fact that the sensing devices accumulate similar sort of data from related sensors. So it is necessary to get rid of the unnecessary data which not only will save the resource consumption and helping in lowering the cost but also will lead to providing improved QoS as traffic load lessens hence the information can be transported in a timely fashion. Discovering the data which are similar in nature and getting rid of them yet ensuring high QoS are few issues that need to be addressed. Following are some of the recent methods that have been proposed to handle these issues.

5.1.1 Techniques for resource efficient data collection

Battery powered smart devices have limited power and storage (Liu et al. 2016). These constraints have led to devise ways to use them in an optimized way for making it run for a longer period of time. In Deligiannakis and Kotidis (2005), the authors have tried to develop a data reduction technique in sensors to reduce the data size by compressing the data. However, they have not tried to correlate the sensor nodes that may help in reducing the accumulated data in the sensors.

One of the data transformation techniques to reduce data size from correlated data is by principal component analysis (Jolliffee 2002). This technique reduces the data size but it does not take into account of the power efficiency or the cost involved in data collection. In Aggarwal et al. (2011), these issues have been addressed. Here the authors have developed a real-time algorithm which takes the functional dependencies of sensors streams into account in real time to reduce the amount of data collected hence data is obtained from a minimal set of sensors.

In [64], the authors have proposed a near real-time and cost-effective data communication in cloud-assisted disaster surrounding. The charm of the proposed work is that it is able to identify similar set of images from huge image dataset and transfer only the unique and representative images and hence helps in lower bandwidth utilization and saving the battery power.

In content-based similarity detection, images are considered to be similar when images of the same scene but with slightly different viewpoints and illuminations are obtained. In SmartEye (Hua et al. 2015), images with similar characteristics are accumulated to form a class containing same label. This results in deduplication of images in the class which can be removed by semantic hashing (Indyk and Motwani 1998) and space-efficient filters (Bloom 1970). This is extremely useful in communicating between phone and remote servers at a much reduced cost. In this method, near duplicate images are not removed but only unique images are uploaded saving bandwidth utilization.

A lot of research has been done on reducing data redundancy by similarity detection in image and videos. In CARE Weinsberg et al. (2012), to enhance the data transfer in limited capacity networks while maintaining the QoS, redundant images are eliminated. In this framework, data is being transmitted in peer-to-peer fashion assuming that central infrastructure is not available as it happens in case of disaster scenarios. A particular node is given the responsibility to compare similarity between the images stored in that node and the images it has received from peers. When the infrastructure connectivity is available in later time then the node transfers the unique image to the central server.

In bandwidth constrained network, Dao et al. Dao et al. (2014) established a technique that aims to identify similarity in images and videos. When a new image is considered to be sent to server, rather than sending the whole image a part of the image (i.e., metadata is extracted) is transmitted over the network to the server. This metadata is compared with the images that were previously received in the server to find similarity between the two images. If similarity is found then the image is not sent for that time else the image is uploaded to the server. The authors have experimented their results in test-bed and simulated their results in NS3, and observed that the successful similarity detection is up to 70% true positive rate and 1% false positive rate.

In real-time mobile crowdsensing system (Sherchan et al. 2012), data collection is done by instantly processing and analyzing of data. Context-Aware Real-time Open Mobile Miner (CAROMM) processed the data based on the context attached to the data and helping in data retrieval from the dataset. This data is obtained from the stream of data sensed by the mobile device's sensor and thus helps in energy saving and reduced use of bandwidth. CAROMM collects and correlates this real-time sensory information with social media data from both Twitter and Facebook and can provide real-time information to queries related to specific location of mobile user.

MCS requires a large amount of data to be stored and transferred across the network. In Roemer et al. (2014), the authors proposed data deduplication strategy to reduce the storage and bandwidth consumption. The idea is to find similarity in the data that needs to be transmitted and the unique data is then sent over the network to the server. This is achieved by data deduplication method which is based on WANs, and compressing of the data to increase the performance of the transmission time. For further improvement of the performance, semantics of the content of the data should have been taken into consideration.

5.1.2 Techniques for achieving good QoS

In this segment we discuss few techniques in mobile crowdsensing that have been proposed by researchers for achieving good QoS.

In Xu et al. (2015), the authors presented Compressive CrowdSensing (CCS)- a framework in MCS which performs compressive sensing techniques. The framework allows the mobile user to gather data on a wide range of large scale phenomenon but with fewer data sample contribution from user at the same time maintaining the acceptable level of accuracy for the MCS system. CCS is also designed to be easily adapted to function in a wide range of crowd systems.

In Yan et al. (2010), an accurate image searching technique known as CrowdSearch for mobile phones is introduced. Automated image searching strategy is integrated with real-time human validation in CrowdSearch where output of local processing on mobile phones and back-end processing of remote servers are combined to implement the process of automated image search. By utilizing Amazon Mechanical Turk, validation of the data is performed by the humans, who actively participate to perform the tasks for certain amount of incentive. But the trade offs, such as energy consumption, delay and incentives are there when validation is done with human. CrowdSearch addresses these issues and provide a prediction algorithm to find the results that needs validating, and also decide when and how this result can be validated. It also maintains the accuracy of the data and responds to search queries in user specified deadline. Experimental results show that CrowdSearch is able to achieve over 95% precision across multiple image categories, furnish desired reply in very less times and costs very little.

Transferring of large amount of crowdsensed data is a tedious task due to the limitations on the resources. In Wang et al. (2014), the authors propose SmartPhoto, a framework for assessing and optimizing the photo selection obtained by a crowdsource. This framework helps to measure the standard (utility) of the crowdsourced photos based on geographical and geometrical information (i.e., metadata) which also includes information of smartphones orientation, location of the phone and various other parameters included in built-in camera of the smartphone. Information regarding the time and location of a photo can be obtained from the analysis of metadata and only the unique and useful photo are to be transmitted. They have also discussed three optimization problems to handle the trade-off between photo utility and resource constraints. They have proposed an efficient solution, and observed the performance limitations of the algorithm. This framework is being tested in android based smartphones. In order to increase the accuracy of metadata they used data fusing, reducing the sensor reading errors and filtering out the false information.

In MCS, the burden of storing and transferring the sensed data is a key challenge. Compressive sensing is useful in such a scenario where it helps to reduce the sampling rate of the sensed data. Location, time, condition of the device and various other factors determine the cost of a specific sample. Only a small subset of the sample is used from the available data and reconstruction the desired information from that subset. In Xu et al. (2015), authors have introduced CACS (cost-aware compressive sensing) framework which uses lower amount of resources. It is able to handle the fluctuations that occur in resource costs and as a result it accumulates fewer sensor data sample that incurs high resource cost but at the same time maintaining randomness to obtain accurate data recovery by compressive sensing. In other words, it balances the minimization of overall sample cost with accuracy to recover the data. It was observed that CACS had a success accuracy of 80% in data reconstruction utilizing only 10% of the energy.

In Li et al. (2015), the authors have investigated the problem of maximizing the total data utility of the sensed data under resource constraint scenario such as MCS. Based on redundancy-aware reverse auction framework they have proposed a combinatorial auction mechanism. This method consists of two parts: an approximation algorithm to determine the winning bids and a critical payment scheme. This method assures of achieving truthfulness of the sensed data, individual rationality, and efficiency in computation under a feasible budget.

Thus, quality of service in terms of quality of the collected data is ensured.

5.1.3 Techniques for reducing energy consumption

In MCS systems, it is essential to reduce the consumption of energy by the smart devices, since consumption of high energy gravely lowers down the participant's willingness (Wang et al. 2018). In this segment, comprehensive reviews of energy saving techniques in MCS are discussed. In MCS, the overall energy consumption can be lowered by lowering the number of recruited participants. In this paper (Zhang et al. 2014), the authors propose a framework named CrowdRecruiter, to select participant for Piggybacking Crowdsensing (PCS). PCS enabled in reducing the individual smart devices energy consumption by performing sensing tasks and transmitting sensed data while making use of call opportunities. CrowdRecruiter ensures spatial-temporal coverage while minimizing the overall payment of incentive by choosing small number of participants. Minimal participant selection under probabilistic coverage constraints is done by CrowdRecruiter in three steps. First, for each mobile user, it forecasts the call and coverage probability. In the next step, for multiple users, estimation of joint coverage probability is done by a utility function. Finally, for incrementally choosing the participants, it deploys an effective low-complexity algorithm. The authors in Xiong et al. (2016) proposed iCrowd, a near- optimal task allocation framework for MCS that is used to formulate a task allocation problem with different incentives, and to maximize k-depth coverage quality while minimizing energy consumption in MCS. It operates in two steps. At first, based on historical records it predicts the call and mobility of the mobile user, and then for each sensing cycle it selects a set of user who would perform the task. In this way, without exceeding the predefined incentive budget, iCrowd is able to obtain a near maximal k-depth coverage. It is also able achieve near-minimal incentive payment while meeting a predetermined k-depth coverage goal.

One way to reduce the energy consumption is to replace traditional sensors with energy efficient sensors. Another way can be to adjust the sampling frequency dynamically. In Cohn et al. (2012), the authors propose a technique by which the need for energy to motion sense is significantly reduced in order of magnitude. Static electric field is being used to passively sense body motion employing ultra-low power method instead of traditional accelerometer based methods. In Wang et al. (2015), the authors have proposed EffSense- an energy-efficient and cost-effective data uploading framework, which works in fixed data uploading cycle while making use of adaptive uploading schemes. The participants are permitted to use distributed decision making scheme in each cycle for taking decision which network to upload and when to upload the data. The users may be a data plan user, who is utilizing some 3G connections for data transfer and non-data plan user, who is utilizing WiFi/ Bluetooth for communication. To participate readily in crowdsensing, data plan user mostly thinks of the energy consumption cost whereas non-data plan user is concerned of the data cost itself. EffSense helps in reducing data cost for non-data plan user by offloading most of the data to Bluetooth/WiFi whereas the cost in data plan user is reduced when data is piggybacked while on call. Proper uploading strategies can be found by EffSense by predicting the users call and mobility.

Another alternative for uploading data more energy-efficiently is catching the opportunities when mobile users place phone calls or use mobile applications. One typical work is Piggyback CrowdSensing (PCS) Lane et al. (2013), a system for collecting mobile sensor data from smartphones that lower the energy overhead of user participation. Their approach is to collect sensor data by exploiting smartphone app opportunities, that is, those times when smartphone users place phone calls or use application. By taking the advantage of opportunistic application run by user, they proposed an energy efficient MCS strategy based on Piggyback CrowdSensing (PCS), where optimal time slot is found through predictive modeling to perform the sensing task. In this approach, when the smartphone is using any application or making a call, the data is collected at that opportunity. This strategy works as the smartphones are already in active state from idle state so less power consumption to wake the smartphone from idle state. Cloud offloading Liu et al. (2012) technique can be utilized to reduce the energy consumption in smart phones where local information can be processed later at the time of data uploading to server. Here the authors have proposed a solution that enables a sensing devices GPS receiver to vigorously duty-cycle and log bare minimum GPS signal for later processing.

The features of the different applications of mobile crowdsensing is summarized as Table 2. The table indicates the commonly used sensors and their associated application features addressed by the existing works.

5.2 Techniques used for mobile crowdsourcing

In the initial years, based on the collaboration of the willing participants, it can be grouped as participatory and opportunistic (Jamil et al. 2015). The participants or the user of MCoS performs the tasks by two ways: direct mode and word of mouth mode (WoM). In direct mode, the control is with the central MCoS platform which accepts the tasks from the end user. Then it breaks down the tasks into sub tasks and allots the subtasks to the willing participants of the crowd for getting the job done. So the end user (human) and the crowd (human) both participate in the process but without having direct interaction with one another. This procedure of indirect interaction may at times be less suitable for certain set of time sensitive and location dependent tasks. In WoM (word of mouth), the willing participants of the crowd employ their friends and known people in their social networking sites to get the tasks done apart from them also performing a part of those tasks. This in turn helps in expanding the coverage area of the crowd. Here unlike direct mode, the co-worker of crowd actively interacts within themselves to perform the complex tasks. This method is more efficient in case of time-sensitive or location dependent tasks.

A task is further categorized into two types, namely, tasks done by the help of human intelligence and the tasks done by the mobile device of the participants of the crowd (Wang et al. 2015). In the first case, it is used in cases where human intelligence is needed to analyze the job. Based on the value of intelligence of the collected data, the tasks of MCoS application can be classified into three sub class : user data, contextual data and social data where user data is generally obtained from individual users personal information, contextual data generally refer to the surrounding information of the user or the semantics of an area, and social data refers to the collection of data generated from social networking sites and this data helps in understanding of the dynamics of the urban population.

The proficiency of the participants also helps in classifying MCoS application. Depending on the involvement of the participants it may be classified into a) opportunistic b) participatory. In the first case (Panichpapiboon and Leakkaw 2016), (Lane et al. 2015), mobile device takes decision by itself when to perform a task. This method is more autonomous and human involvement is minimal. In the latter case (Hamilton et al. 2011), (Ruiz Correa et al. 2017), (Shin et al. 2014), participation of the crowd is much more and it requires the involvement of human intelligence as well. Based on the location awareness, MCoS application may be divided into real and digital location. In digital world, the real time location of the crowd is not required and the work can be done at any time and from any geographical location. In real-time location, the crowd participants have to be physically present with the mobile device at the particular time to perform the allotted task. This is also called spatial crowdsourcing. Few applications (Sims et al. 2016), (Besaleva et al. 2013) require strong knowledge of the tasks that needs to be completed by the crowd and in other cases minimal knowledge or non-expert may also be able to perform the assigned task.

In opportunistic networks, the job flow in MCoS can be of two types Phuttharak and Loke (2016): a) point-to-point and b) multicast. In the first scenario, the nodes communicate with one another directly and communication from one node to another is done one at a time. In the second, there may be one to many parallel connections. The communications between the crowd and the crowd processing platform may be heterogeneous in nature. But the network may be centralized, decentralized or it may be hybrid in nature Phuttharak and Loke (2019). In centralized method, the data is collected from the participants and then further processed in the nearest server which may be cloud or crowd processing platform. In decentralized method, the data is being processed in the nodes itself before transmitting it to the server. Hybrid method provides a mid-way between former two methods where the very important and real-time sensitive data are processed in the node and the rest is transmitted over the network for further processing. In this way this method is able to handle real-time sensitive data. The incentive for data collection can be intrinsic or extrinsic motivation (Kaufmann et al. 2011). Intrinsic motivation can be factors such as enjoyment or self-satisfaction whereas the extrinsic can be related to monetary benefits or social obligations. The data that is collected by the sensors needs to be analysed and processed for providing the solution to

Table 2 Comparison of existing works on the applications of Mobile Crowdsensing

Area/cate-gory	Appname/Refer-ence	Purpose	Sensors Used	Data wisdom (collec-tive(C) or indiv- idual (I))	Involv-ement(Opper-tunistic(O) orpartic-ipatory(P))	Ince- ntive	Platf-orm(Andr-oid(A)oriOS)
Social& network-knowle-dgeshar-ing	Crowd-Smile Punjabi et al. (2013)	This is a system for accessing & reusing of crowdsourced data. It is based on social & mobile integrated system.	Human, GPS	I	P	Money	A
	Crowd-Found Harburg et al. (2015)	Developed to find lost item, theuser input the details on a map& send the notifica-tion tocrowd user who are on thesame route as well as near themissing item.	Human, GPS	I	P	Money	–
	Eilander et al. (2016)	Based on mobile crowdsourc-ing, uses filtering and geo-statistical methods for plotting a digital elevation map, flood probability map can be con-structed.	Human, Camera	I	P	Ethical	–

Table 2 (continued)

Area/cate-gory	Appname/Refer-ence	Purpose	Sensors Used	Data wisdom (collec-tive(C) or indiv- idual (I))	Involv-ement(Opper-tunistic(O) orpartic-ipatory(P))	Ince- ntive	Platf-orm(Andr-oid(A)oriOS)
Enviro-nmen-talMoito-ring &utilities	Ear-Phone Rana et al. (2010)	Enviromental data such as noise of urban area is crowdsourced, user can get noise level by a noise map from the crowdsou-rced data.	GPS, Micro-phone	I	O	Ethical	A
	Matsuyama et al. (2014)	Builds database containing sounds of environments. User records the sounds by the smartphone &send to the cloud.	GPS, Micro-phone	I	P	–	A
	Cicada Hunt (2022)	Helps user to identify species of bug. When a bug is nearby, the application listens for a short period of time & detectsthe particular species basedon the sound it makes.	GPS, Micro-phone	I	P	–	Both
	Victorino and Estuar (2014)	Developed to help in contrib-uting to flood monitoring & public awareness. It allows thecrowd to report flood levels in various locations.	Human, GPS, Camera	I	P	–	A
	Yang et al. (2014)	It allows the user to have docu-mentation of potentialhazard or hazard that has happened helping user to fixbefore acci-dents can happen.	Human, GPS, Camera	I	P	–	A
	Zhang et al. (2018)	The crowdsourced noise data obtained is filtered & corrected,guarantee certain qualityof labels of noisy data.	Human, Micro-phone	C	P	–	-
	Mccallum et al. (2018)	Gamification is used to make the crowd participate in environ-mental monitoring	Human, Camera	I	P	Prize	Both
	Open-Signal OpenSignal Android App (2022)	Builds a picture of the netw-ork as experienced by users,rather than the sometimesinaccurate methodologies usedby mobile carriers.	GPS, Human	I	P	–	Both

Table 2 (continued)

Area/cate-gory	Appname/Refer-ence	Purpose	Sensors Used	Data wisdom (collec-tive(C) or indiv- idual (I))	Involv-ement(Opper-tunistic(O) orpartic-ipatory(P))	Ince- ntive	Platf-orm(Andr-oid(A)oriOS)
TrafficNaviga-tion &UrbanSensing	Grazioli et al. (2013)	Used in smart parking manage-ment.	Human, GPS	I	P	Ethical	-
	Navi-Tweets Kwak et al. (2014)	Used in vehicles route choices.	GPS	I	P	Ethical	A
	TeleEye Fan et al. (2013)	Helps user to inquire informa-tion regardinglocation.User will get theanswer through otheruser at inquired location.	GPS	I	P	Ethical	A
	Kamino Kamino- Local walking (2022)	Guides travelers & urbanexplor-ers on where to go& what to do based oncrowdsourced data	Human, Camera	C	P	Ethical	iOS
	Boss et al. (2018)	Spatial analysis methodused to locate cyclistdistribution in city	GPS, Human	I	P	Ethical	Both
	Mobile 3D modeler Eaglin et al. (2013)	Helps user to build a3D model of the inte-rnal structure of a building	Human	I	P	Money	iOS
	Indoor-Crowd Chen et al. (2014)	Helps indoor 3D maps recon-structions.	GPS, sensor, camera	C	P	–	iOS
Trans-lation	Twitter-One Gimpel et al. (2011)	Part-of-speech taggingfor Eng-lish data from Twitter	Human	C	P	Money	-
	Unbabel Unbabel - Machine (2019)	Offers an onlinetranslation service	Human	C	P	Money	Both
Disaster Report	Wang et al. (2018)	Hyper resolution dataobtained to addressurban flooding.	Human, Camera	I	P	Ethical	Both
	Eilander et al. (2016)	Using filtering & geo-statistical methods forplotting elevation map &flood probability map.	Human, camera	I	P	Ethical	-
	iShake Reilly et al. (2013)	Used to obtain dataon ground motion measurements.	GPS, accelero meter, gyroscope	C	P	Ethical	iOS
	Crowd-Help Besaleva and Weaver (2014)	Used for helping peoplein disas-ter sites.	GPS, accelero meter, gyro-scope	C	P	Ethical	-
HealthMonit-oring	Yi et al. (2012)	Used for monitoringof health by BSN	Accelero meter, Temper-ature Sensor	I	O	Ethical	A
	Diet-Sense Reddy et al. (2007)	To obtain dietary pattern for studying chronicdiseases related to foodhabit.	Human, Micro-phone, Camera	I	P	Ethical	A

Table 2 (continued)

Area/cate-gory	Appname/Refer-ence	Purpose	Sensors Used	Data wisdom (collec-tive(C) or indiv- idual (I))	Involv-ement(Opper-tunistic(O) orpartic-ipatory(P))	Ince- ntive	Platf-orm(Andr-oid(A)oriOS)
Public Safety	Ballesteros et al. (2015) iSafe	Provide personalized & context aware recommendations to mobile user for safety.	Human, GPS	I	P	Ethical	A
	[Trans-Safe] Hamilton et al. (2011)	Used for safety of public	Human, GPS	C	P	Ethical	iOS

the third parties who has asked for getting the solution for a given task. The processing of MCoS can be divided into 1) worker selection, 2) workflow control and 3) analysis (Phuttharak and Loke 2019)

1) Worker selection: In MCoS application, tasks when allocated to the crowd, it should be noted that the workers should be competent enough to finish the tasks efficiently maintaining the quality. The workers of the crowd may be active or passive. Active workers participate in the crowdsourcing tasks which may also be spatial in nature. For example, Uber[2], Grab[3], Lyft[4] use crowdsourcing platform to check and match the tasks to the workers available in the particular geographical location and allot the task accordingly to the available worker. Passive workers on the other hand do not actively participate and hence the application runs in the workers mobile device in the background. After completion of the tasks it is then automatically transmitted all of course, with the permission of the passive worker.
2) Workflow Control: Workflow control refers to how the assigned tasks can be planned and then implemented to solve a given task by the crowd. Workflow aids in dividing a task into smaller tasks, distribute the tasks to crowd workers and afterwards collect the distributed completed tasks and join them to form the total solved task. The three ways that can be done are Phuttharak and Loke (2019):- i) Divide and conquer, where the work is divided and distributed for solving the task, ii) Iterative where the quality of the task is improved by employing multiple workers to the existing solved task, iii) Redundancy based quality control where a particular set of task is performed by a group of efficiently skilled workers and the most common solution is considered the accepted solution.
3) Analysis: This is important to increase the quality as well as choosing the best solution from the set of solutions provided by the workers of the crowd. This can be done by basic or advanced approach. Basic approach can be majority voting, majority rating and integration aggregation. In Schenk and Guittard (2012), aggregation can be done in two way: integrative where the value is obtained by pooling complimentary large number of inputs and selective values can be obtained by getting set of options from the crowd. Advanced approach utilizes data mining, machine learning and other sophisticated techniques to have the idea of the data being crowd-

[2] https://www.ubereats.com.

[3] https://www.grab.com/.

[4] https://www.lyft.com/.

sourced. Big data plays a major part in analysis technique of these data which may be structured or unstructured, historical or real-time data and then further be used for comparing the data for obtaining more compact and complete solution (Pilloni 2018).

The representative works on MCS and MCoS pertaining to different application domains have been compared in Table 3. It has been observed that data collection from a wide variety of users has been a major obstacle in testing most of these systems. For convenience, the challenges addressed by these works is presented w.r.t the challenges listed in Fig. 9.

6 Future research directions

Mobile Crowdsensing and Mobile Crowdsourcing are research domains with great potential leading to a wide spectrum of real life applications. It is predicted that by connecting the willing workers to the tasks through MCS and MCoS platforms can increase the global GDP. Business models are changing to suit the present scenario where crowd workers are hired for performing the tasks. However, improvements are possible in the architecture and implementation of MCS and MCoS. Some of the issues in existing works have been highlighted in Table 3. Few research challenges have also been put forward. The prospective research problems include, but are not limited to:

- Preserving Privacy: With machine intelligence techniques in place, anonymity or geocasting (To et al. 2014) are not sufficient to preserve the privacy of the participants of MCoS and MCS. New forms of privacy threats such as, model inversion attacks may lead to estimation of sensitive information about the behavioral traits of the participants. Thus, it is challenging to preprocess the data in a way that only the meaningful insight reaches the server for analysis by the MCoS applications. However, the preprocessed data can no longer be analyzed to extract any sensitive information about the users. Differential privacy models can be applied as it is a strong notion of privacy. Novel preprocessing techniques are needed to be designed to preserve the privacy without hampering the precision of the MCoS and MCS applications.
- Utilizing edge vs cloud: In order to save the network bandwidth a new trend can be observed, that of computing closer to the data source. Edge computing and intelligence at the edge is a new research paradigm that can be highly useful in attaining performance while handling data scalability issue at the cloud. Edge servers are typically placed closer to the data sources, thus, location awareness and response time are two inherent advantages of such solutions. So, for responding to local phenomena, edge services can pose to be effective for MCS and MCoS solutions while data can be opportunistically sent to the cloud servers as demanded by the applications.
- Context aware sensing: The main problem with participatory sensing is that the dataset may contain noisy data if data are not recorded in appropriate sensing context. In most of the cases, the usability of the data collected through participatory sensing depends on the smartphone sensing context. For some applications, good quality data is collected only if the phone is carried in a specific way like kept in hand. Thus, context aware data collection and data cleaning techniques are required for better utilization of the sensing data.
- Real time streaming: In some MCS and MCoS applications, streaming data could be generated through thousands of participants. Efficient approaches are required for storing and processing of the streams of real time data. Designing applications to scale is important in working with real time streaming data. It is also challenging to determine the sequence of data in a data stream. Fault tolerant system is required to handle the data coming from different sources and locations, and in different formats and volumes.
- Cost and quality tradeoff: The cost can be computed in terms of computational cost, cost of communication (transfer of data between mobile devices, edge nodes, and the cloud), and identification of the computational node. Finding a cost effective solution, that is, an approach that minimises one or more of these costs, can result in a compromise in the quality of service (QoS). For example, compressing data at mobile devices before communicating to edge nodes/cloud to reduce the amount of storage needed can result in data loss. Thus, finding the perfect balance between cost effectiveness and maintaining a benchmark QoS is an open research problem for MCS and MCoS till date.

7 Conclusion

Smartphones present a unique combination of sensing, communication, and computation that opens up the emerging application paradigms called crowdsensing and crowdsourcing. In our research we have tried to understand the difference between the two techniques which are often interchangeably used. As the world is moving towards an environment where each device with an internet facility can be connected over internet, these two techniques will be utilized a lot more to provide a better standard of living. So here, in our work, we studied various problems that are

Table 3 Comparative analysis of Mobile Crowdsourcing and Mobile Crowdsensing works w.r.t challenges addressed

Public- ation	Year	Target Applic- ation	Type	Cases	MCS/ MCoS	Challenges addressed	Comments
Samulowska et al. (2021)	2021	Enviro- nmental	Real data	Air Pollu- tion	MCoS	Quality Control: QA framework is proposed for finding the most robust data quality assurance system.	Limited sample size may lead to erroneous conclusion.
Dutta et al. (2017)	2017		Real data	Noise Pollut- ion	MCoS	Spatial Crowd- sourcing and Obstructive Mobile Context: Acquiring real time, context aware and spatially fine- grained noise pollution data to generate pollution footprint map.	Data collection process depends on mobility of participants which may lead to spatially sparse dataset. Hence gener- ating high granularity spatial pollution map becomes difficult.
Breda and Patel (2021)	2021	Health care	Real data	Fever monit- oring	MCS	Heterogeneous nature of data and sensors: Ubiquitous body tem- perature measurement through smart- phone sensors.	Tested mainly on a few febrile users. So, quality of sensing may not be assured.
Yang et al. (2020)	2020	Survei- llance	Simul- ated data	Detect- ion of explo- sive	MCS	Spatial Crowd- sourcing: Spatio -temporal analy- sis to provide high detection accuracy through a two- level feedback loop.	Only one type of sensor is used which detects a particular type of chemical explosive.
Staniek (2021)	2021	Smart traffic monitoring	Real data	Traffic condition and pavement manage- ment.	MCoS	Quality Control: Evaluates the road pavement condition and volume of traffic and distribu- tion in freight transport.	Each vehicle class should be sepa- rately treated for more reliable prediction. Implemented only in Android devices.

being faced while implementing, also few solutions proposed by various researchers has been discussed. We have also talked about various condition based techniques and discussed how each parameter i.e., condition will have an effect on the crowdsourcing or crowdsensing. In future, we are looking into mechanisms to merge these two paradigms to not only sense and send data or opinion, but to provide end-to-end services through edge for a smart connected society.

Declaration

Conflict of interest The authors declare that there is no conflict of interest.

References

http://www.cs.cmu.edu/afs/cs/project/spirit-1/www/
https://wiser.nlm.nih.gov/
https://www.businessnewsdaily.com/4134-what-is-crowdfunding.html
Abu-Elkheir, M., Hassanein, H. S., Oteafy, S. M. A.: Enhancing emergency response systems through leveraging crowdsensing and heterogeneous data. (2016) International Wireless Communications and Mobile Computing Conference (IWCMC), pp: 188-193, https://doi.org/10.1109/IWCMC.2016.7577055
Afridi, A.: Crowdsourcing in mobile: A three stage context based process. In: IEEE Ninth International Conference on Dependable, Autonomic and Secure Computing (DASC), pp. 242–245. AUS, December, Sydney (2011)
Aggarwal, C. C., Xie, Y., Yu, P. S.: On dynamic data-driven selection of sensor streams. In Proc. of KDD, pages 1226–1234 (2011)
Allahbakhsh, M., Benatallah, B., Ignjatovic, A., Motahari Nezhad, H.R., Bertino, E., Dustdar, S.: Quality control in crowdsourcing systems: issues and directions. J. IEEE Internet Comput. **17**(2), 76–81 (2013). https://doi.org/10.1109/MIC.2013.20
An, J., Gui, X., Wang, Z., Yang, J., He, X.: A crowdsourcing assignment model based on mobile crowd sensing in the internet of things. IEEE Internet Things J. **2**(5), 358–369 (2015)
Atzori, L., Girau, R., Martis, S., Pilloni, V., Uras, M.: A siot-aware approach to the resource management issue in mobile crowdsensing. In 20th Conference on Innovations in Clouds, Internet and Networks (ICIN), March 2017, pp. 232–237 (2017)
Balasubramanian, N., Balasubramanian, A., Venkataramani, A.: Energy consumption in mobile phones: A measurement study and implications for network applications. In Proceedings of the 9th ACM SIGCOMM Conference on Internet Measurement Conference, ser. IMC '09. pp. 280–293, New York, NY, USA (2009)
Ballesteros, J., Carbunar, B., Rahman, M., Rishe, N., Iyengar, S.: Towards safe cities: A mobile and social networking approach. 25(9), 2451 - 2462. https://doi.org/10.1109/TPDS.2013.190 (2015)
Barik, R. K., Patra, S. S., Patro, R., Mohanty, S. N., Hamad, A. A.: GeoBD2: Geospatial big data deduplication scheme in fog assisted cloud computing environment. In conference proceedings of 8th International Conference on Computing for Sustainable Global Development (INDIACom). pp. 35-41. March (2021)
Besaleva, L. I., Weaver, A. C.: CrowdHelp: mHealth Application for Emergency Response Improvement through Crowdsourced and Sensor-Detected Information. In Proceedings of Wireless Telecommunications Symposium. Washington, DC, USA. June. https://doi.org/10.1109/WTS.2014.6835005 (2014)
Besaleva, L. I., Weaver, A. C.: Crowdhelp: A crowdsourcing application for improving disaster management. In Proc. of IEEE Global Humanitarian Technology Conference (GHTC), pp. 185–190, October (2013)
Bloom, B.: Space/time trade-offs in hash coding with allowable errors. Proc. Commun. ACM **13**(7), 422–426 (1970)
Boss, D., Nelson, T., Winters, M., Ferster, C.J.: Using crowdsourced data to monitor change in spatial patterns of bicycle ridership. J Trans Health **9**, 226–233 (2018)
Boutsis, I., Kalogeraki, V.: Crowdsourcing under real-time constraints. In Proc. of the IEEE 27th International Symposium on Parallel & Distributed Processing (IPDPS). May. https://doi.org/10.1109/IPDPS.2013.84 (2013)
Breda, J., Patel, S.: Intuitive and Ubiquitous Fever Monitoring Using Smartphones and Smartwatches. https://arxiv.org/abs/2106.11855v1 (2021)
Capponi, A., Fiandrino, C., Kantarci, B., Foschini, L., Kliazovich, D., Bouvry, P.: A survey on mobile crowdsensing systems: Challenges, solutions, and opportunities. IEEE Commun. Surv. Tutor. **21**(3), 2419–2465 (2019)
Chamberlain, J., Kruschwitz, U., Poesio, M.: Optimising crowdsourcing efficiency: Amplifying human computation with validation. J. Inf. Technol. **60**(1), 41–49 (2018)
Chen, Z., Fiandrino, C., Kantarci, B.: On blockchain integration into mobile crowdsensing via smart embedded devices: A comprehensive survey. In Journal of Systems Architecture: the EUROMICRO Journal. 115(C). https://doi.org/10.1016/j.sysarc.2021.102011 (2021)
Chen, S., Li, M., Ren, K.: The power of indoor crowd: Indoor 3D maps from the crowd.In Proc. of IEEE Conf. Comput. Commun. Work (INFOCOM WKSHPS), pp. 217–218, April (2014)
Chen, G., Kotz, D.: A survey of context-aware mobile computing research. A technical report published by ACM, Hanover, NH, USA, Tech. Rep (2000)
Chon, Y., Lane, N. D., Li, F., Cha, H., Zhao, F.: Automatically characterizing places with opportunistic crowdsensing using smartphones. In Proc. of ACM UbiComp, pp.481–490, New York, NY, USA (2012)
"Cicada Hunt Is Like Shazam for Insect Sounds", https://mashable.com/2013/08/30/cicada-hunt-app/.Accessed 13 Feb 2022
Cohn, G., Gupta, S., Lee, T., Morris, D., Smith, J.R., Reynolds, M.S., Tan, D.S., Patel, S.N.: An Ultra-Low-Power Human Body Motion Sensor Using Static Electric Field Sensing. In Proc. of ACM Conf. Ubiquitous Comput. Sept. **2012**, 99–102 (2012)
Cornelius, C., Kapadia, A., Kotz, D., Peebles, D., Shin, M., Triandopoulos, N.: Anonysense: Privacy-aware people-centric sensing. In Proc.of ACM MobiSys, pp. 211–224, New York, NY. https://doi.org/10.1145/1378600.1378624 (2008)
Dao, T., Roy-Chowdhury, A. K., Madhyastha, H. V., Krishnamurthy, S. V., Porta, T. L.: Managing redundant content in bandwidth constrained wireless networks. In Proc. of CoNEXT, pages 349–361 (2014)
Dasari, V.S., Kantarci, B., Pouryazdan, M., Foschini, L., Girolami, M.: Game Theory in Mobile CrowdSensing: A Comprehensive Survey. J. Sens.**20**(7), 2055 (2020)
Deligiannakis, A., Kotidis, Y.: Data Reduction Techniques in Sensor Networks. Proc. IEEE Data Eng. Bull. **28**(1), 19–25 (2005)
Dighriri, M., Lee, G.M., Baker, T.: Measurement and Classification of Smart Systems Data Traffic Over 5G Mobile Networks, pp. 195–217. Springer International Publishing, Cham (2018)

Dinh, H.T., Lee, C., Niyato, D., Wang, P.: A survey of mobile cloud computing: architecture, applications, and approaches. J. Wirel. Commun. Mobile Comput. **13**(18), 1587–1611 (2013)

Dow, S., Kulkarni, A., Klemmer, S., Hartmann, B.: Shepherding the crowd yields better work. In Proceedings of the ACM 2012 Conference on Computer Supported Cooperative Work, ser. CSCW '12. New York, NY, USA: ACM, 2012, pp. 1013–1022 (2012)

Du, H., Yu, Z., Yi, F., Wang, Z., Han, Q., Guo, B.: Recognition of group mobility level and group structure with smart devices. IEEE Trans. Mobile Comput. **17**(4), 884–897 (2018)

Dutta, J., Pramanik, P., Roy, S.: NoiseSense: Crowdsourced Context Aware Sensing for Real time Noise Pollution Monitoring of the City. In IEEE International Conference on Advanced Networks and Telecommunications Systems (ANTS) (2017). https://doi.org/10.1109/ANTS.2017.8384103

Eaglin, T., Subramanian, K., Payton, J.: 3D modeling by the masses: A mobile app for modeling buildings. In Int. Conf. Pervasive Comput. Commun. Work. PERCOM Work., pp. 315–317, March (2013)

Ebinazer, S.E., Savarimuthu, N., Bhanu, M.S.: ESKEA: enhanced symmetric key encryption algorithm based secure data storage in cloud networks with data deduplication. Int. J. Wirel. Personal Commun. **117**(4), 3309–3325 (2021). https://doi.org/10.1007/s11277-020-07989-6

Eilander, D., Trambauer, P., Wagemaker, J., van Loenen, A.: Harvesting social media for generation of near real-time flood maps. In Proc of 12th International Conference on Hydroinformatics (HIC 2016) Smart Water for the Future **154**, 176–183 (2016)

Fan, Y.C., Iam, C.T., Syu, G.H., Lee, W.H.: TeleEye: Enabling Real-time Geospatial Query Answering with Mobile Crowd. In IEEE Int. Conf. Distrib. Comput. Sens. Syst. **1**(d), 323–324 (2013)

Feng, W., Yan, Z., Zhang, H., Zeng, K., Xiao, Y., Hou, Y.T.: A survey on security, privacy, and trust in mobile crowdsourcing. IEEE Internet Things J. **5**(4), 2971–2992 (2017)

Gadiraju, U., Kawase, R., Dietze, S., Demartini, G.: Understanding malicious behavior in crowdsourcing platforms: the case of online surveys. Proc. ACM CHI'15. pp: 1631- 1640. https://doi.org/10.1145/2702123.2702443 (2015)

Ganti, R., Ye, F., Lei, H.: Mobile Crowdsensing: Current State and Future Challenges. IEEE Commun. Magaz. **49**(11), 32–39 (2011)

Gao, R., Sun, F., Xing, W., Tao, D., Fang, J., Chai, H.: CTTE: Customized Travel Time Estimation via Mobile Crowdsensing. In IEEE Transactions on Intelligent Transportation Systems, pp: 1-13, https://doi.org/10.1109/TITS.2022.3160468 (2022)

Gao, G., Wu, J., Xiao, M., Chen, G.: Combinatorial Multi-Armed Bandit Based Unknown Worker Recruitment in Heterogeneous Crowdsensing. In IEEE INFOCOM 2020 - IEEE Conference on Computer Communications, pp: 179-188, https://doi.org/10.1109/INFOCOM41043.2020.9155518 (2020)

Geiger, D., Seedorf, S., Schulze, T., Nickerson, R., Schader, M.: Managing the crowd: Towards a taxonomy of crowdsourcing processes. In 17th Americas Conference on Information Systems, Detroit, Michigan, USA, August (2011)

Gimpel, K., Schneider, N., OConnor, B., Das, D., Mills, D., Eisenstein, J., Heilman, M., Yogatama, D., Flanigan, J., Smith, N. A.: Part-of-speech tagging for twitter: annotation, features, and experiments. In Proc. of the 49th Annual Meeting of the Association for Computational Linguistics: Human Language Technologies (2011)

Gorlatova, M., Sarik, J., Grebla, G., Cong, M., Kymissis, I., Zussman, G.: Movers and shakers: Kinetic energy harvesting for the internet of things. In Proc. of SIGMETRICS, pages 407–419, Austin, June (2014)

Grazioli, A., Picone, M., Zanichelli, F., Amoretti, M.: Collaborative Mobile Application and Advanced Services for Smart Parking . In 14th Int. Conf. Mob. Data Manag., pp. 39–44, June (2013)

Guo, B., Wang, Z., Yu, Z., Wang, Y., Yen, N.Y., Huang, R., Zhou, X.: Mobile crowd sensing and computing: The review of an emerging human-powered sensing paradigm. ACM CSUR **48**(1), 1–31 (2015)

Guo, B., Yu, Z., Chen, L., Zhou, X., Ma, X.: Mobigroup: Enabling lifecycle support to social activity organization and suggestion with mobile crowd sensing. IEEE Trans. Hum.-Mach. Syst. **46**(3), 390–402 (2016)

Guo, B., Yu, Z., Zhou, X., Zhang, D.: From Participatory Sensing to Mobile Crowd Sensing. In Proc, Of Second IEEE International Workshop on Social and Community Intelligence (2014)

Hamilton, M., Salim, F., Cheng, E., Choy, S. L.: Transafe: a crowdsourced mobile platform for crime and safety perception management. In Proc. of IEEE International Symposium on Technology and Society (ISTAS), pp. 1–6, May (2011)

Harburg, E., Kim, Y., Gerber, E., Zhang, H.: CrowdFound: a mobile crowdsourcing system to find lost items On-the-Go. In Proc. of the 33rd Annual ACM Conference Extended Abstracts on Human Factors in Computing Systems (2015)

He, S., Shin, D.H., Zhang, J., Chen, J.: Toward optimal allocation of location dependent tasks in crowdsensing. IEEE INFOCOM. July, In Proc (2014). https://doi.org/10.1109/INFOCOM.2014.6848001

Hirth, M., Hoßfeld, T., Tran-Gia, P.: Analyzing costs and accuracy of validation mechanisms for crowdsourcing platforms. Elsivier J. Math. Comput. Model.**57**(11–12), 2918–2932 (2013)

Ho, C.J., Jabbari, S., Vaughan, J. W.: Adaptive task assignment for crowdsourced classification. In Proceedings of the 30th International Conference on Machine Learning (ICML-13) , pp. 534–542, Atlanta, USA, June (2013)

Hu, X., Li, X., Ngai, E.C.H., Leung, V.C.M., Kruchten, P.: Multidimensional context-aware social network architecture for mobile crowdsensing. IEEE Commun. Magaz. **52**(6), 78–87 (2014)

Hua, Y., He, W., Liu, X., Feng, D.: Smarteye: Real-time and efficient cloud image sharing for disaster environments. In INFOCOM, 2015 (2015)

Huang, C., Lu, R., Zhu, H.: Privacy-friendly spatial crowdsourcing in vehicular networks. J. Commun. Inf. Netw. **2**(2), 59–74 (2017)

Indyk, P., Motwani, R.: Approximate nearest neighbors: towards removing the curse of dimensionality. In Proc. of STOC (1998)

Jamil, S., Basalamah, A., Lbath, A., Youssef, M.: Hybrid participatory sensing for analyzing group dynamics in the largest annual religious gathering. In Proceedings of the 2015 ACM International Joint Conference on Pervasive and Ubiquitous Computing, ser. UbiComp '15. New York, NY, USA: ACM, 2015, pp. 547–558 (2015)

Jolliffee, I.T.: Book named Principal Component Analysis. Springer (2002)

"Kamino- Local walking turs, wherever you are! on the App Store on iTunes". [Online]. https://itunes.apple.com/us/app/kamino-local-walking-tours/id. [Accessed: 13-February-2022]

Kathpal, A., John, M., Makkar, G.: Distributed duplicate detection in post-process data de-duplication. Presented at the (2011)

Kaufmann, N., Schulze, T., Veit, D.: More than fun and money. Worker motivation in crowdsourcing. A study on mechanical turk. In proceedings of Americas Conference on Information Systems. (AMCIS). pp. 1-12. August (2011)

Kim, Y., Kim, C., Lee, S., Kim, Y.: Design and Implementation of Inline Data Deduplication in Cluster File System. In proceedings of KIISE Transactions on Computing Practices, Volume 22(8), 369-374. August (2016)

Kong, X., Liu, X., Jedari, B., Li, M., Wan, L., Xia, F.: Mobile crowdsourcing in smart cities: Technologies, applications, and future challenges. IEEE Internet Things J. **6**(5), 8095–8113 (2019)
Kraut, R.E., Resnick, P.: Building successful online communities. The MIT Press (2012)
Krontiris, I., Dimitriou, T.: Privacy-respecting discovery of data providers in crowd-sensing applications. In Proceedings of the DCoSS (2013)
Kwak, D., Kim, D., Liu, R., Iftode, L., Nath, B.: Tweeting Traffic Image Reports on the Road. In Proc. of 6th Int. Conf. Mob. Comput. Appl. Serv., pp. 40–48 (2014)
Lane, N. D., Chon, Y., Zhou, L., Zhang, Y., Li, F., Kim, D., Ding, G., Zhao, F., Cha, H.: Piggyback crowdsensing (pcs): Energy efficient crowdsourcing of mobile sensor data by exploiting smartphone app opportunities. In Proc. of SenSys, Rome, November. Article 7 (2013)
Lane, N. D., Georgiev, P., Qendro, L.: Deepear: Robust smartphone audio sensing in unconstrained acoustic environments using deep learning. In Proceedings of the 2015 ACM International Joint Conference on Pervasive and Ubiquitous Computing, ser. UbiComp '15. New York, NY, USA: ACM, 2015, pp. 283–294 (2015)
Li, J., Zhu, Y., Yu, J., Zhang, Q., Ni, L.: Towards redundancy-aware data utility maximization in crowdsourced sensing with smartphones. In Proc. of ICDCS (2015)
Li, Q., Varshney, P. K.: Optimal crowdsourced classification with a reject option in the presence of spammers. In Proc. of IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP). September. https://doi.org/10.1109/ICASSP.2018.8461615 (2018)
Lin, Y., Cai, Z., Wang, X., Hao, F., Wang, L., Sai, A.M.V.V.: Multi-Round Incentive Mechanism for Cold Start-Enabled Mobile Crowdsensing. IEEE Trans. Veh.Technol. **70**(1), 993–1007 (2021). https://doi.org/10.1109/TVT.2021.3050339
Liu, Y., Kong, L., Chen, G.: Data-oriented mobile crowdsensing: A comprehensive survey. IEEE Commun. Surv. Tutorials **21**(3), 2849–2885 (2019)
Liu, Y., Lehdonvirta, V., Alexandrova, T., Liu, M., Nakajima, T.: Engaging social medias: case mobile crowdsourcing. In Proc. of the First International Workshop on Social Media Engagement (SoME) (2012)
Liu, J., Shen, H., Narman, H. S., Chung, W., Lin, Z.: A Survey of Mobile Crowdsensing Techniques: A Critical Component for The Internet of Things. In 25th International Conference on Computer Communication and Networks (ICCCN). https://doi.org/10.1109/ICCCN.2016.7568484 (2016)
Liu, J., Yu, L., Shen, H., He, Y., Hallstrom, J.: Characterizing data deliverability of greedy routing in wireless sensor networks. In Proc, Of SECON, Seattle, June (2015)
Liu, J., Priyantha, B., Hart , T., Ramos, H.S., Loureiro , A. A. F., Wang, Q.: Energy Efficient GPS Sensing with Cloud Offloading. In Proc. of 10th ACM Conf. Embedded Network SensorSystems, pp. 85–98, November (2012)
Lu, J., Zhang, Z., Wang, J., Li, R., Wan, S.: A Green Stackelberg-game Incentive Mechanism for Multi-service Exchange in Mobile Crowdsensing. In ACM Trans. Internet Technol. Article 31, pp: 1-29. May. https://doi.org/10.1145/3421506 (2022)
Lupión, M., Medina-Quero, J., Sanjuan, J. F., Ortigosa, P. M.: DOLARS, a Distributed On-Line Activity Recognition System by Means of Heterogeneous Sensors in Real-Life Deployments-A Case Study in the Smart Lab of The University of Almería. In the journal of Sensors. 21(2).https://doi.org/10.3390/s21020405 (2021)
Matsuyama, M., Nisimura, R., Kawahara, H.: Development of a Mobile Application for Crowdsourcing the Data Collection. In Proc of International Conference on Human Interface and the Management of Information **2014**, 514–524 (2014)
Mccallum, I., See, L., Sturn, T., Salk, C., Perger, C., Durauer, M., Karner, M., Moorthy, I., Domian, D., Schepaschenko, D., Fritz, S.: Engaging citizens in environmental monitoring via gaming. In International Journal of Spatial Data Infrastructures Research, 13 (2018)
Messinger, P.R., Stroulia, E., Lyons, K., Bone, M., Niu, R.H., Smirnov, K., Perelgut, S.: Virtual worlds-past, present, and future: New directions in social computing. Decis. Support Syst. **47**(3), 204–228 (2009)
Meyer, D. T., Bolosky, W. J.: A Study of Practical Deduplication. In ACM journals, ACM transaction on storage. Volume 7, No 4. January (2012)
Mohan, P., Padmanabhan, V., Ramjee, R.: Nericell: rich monitoring of road and traffic conditions using mobile smartphones. In SenSys, 2008 (2008)
Neves, F., Finamore, A., Henriques, R.: Efficient discovery of emerging patterns in heterogeneous spatio temporal data from mobile sensors. In MobiQuitous 2020 - 17th EAI International Conference on Mobile and Ubiquitous Systems: Computing, Networking and Services (MobiQuitous '20) Association for Computing Machinery, New York, NY, USA, pp: 158–167. https://doi.org/10.1145/3448891.3448949 (2020)
"OpenSignal Android App-OpenSignal." [Online]. https://opensignal.com/android. Accessed 13 Feb 2022
Panichpapiboon, S., Leakkaw, P.: Traffic sensing through accelerometers. Proc. IEEE Trans. Veh. Technol. **65**(5), 3559–3567 (2016)
Pantic, M., Pentland, A., Nijholt, A., and Huang, T. S.: Human computing and machine understanding of human behavior: A survey. In Artifical intelligence for human computing (pp. 47-71). Springer, Berlin, Heidelberg (2007)
Peng, X., Gu, J., Tan, T.H., Sun, J., Yu, Y., Nuseibeh, B., Zhao, W.: Crowdservice: Optimizing mobile crowdsourcing and service composition. ACM Trans. Internet Technol. **18**(2), 19:1-19:25 (2018)
Phuttharak, J., Loke, S.: Mobile crowdsourcing in peer-to-peer opportunistic networks: Energy usage and response analysis. J. Netw. Comput. Appl. **66**, 137–156 (2016)
Phuttharak, J., Loke, S.W.: A Review of Mobile Crowdsourcing Architectures and Challenges: Toward Crowd-Empowered Internet-of-Things. IEEE Access **7**, 304–324 (2019). https://doi.org/10.1109/ACCESS.2018.2885353
Pietschmann, S., Mitschick, A., Winkler, R., Meissner, K.: Croco: Ontology-based, cross-application context management. In 3rd International Workshop on Semantic Media Adaptation and Personalization (2008)
Pilloni, V.: How data will transform industrial processes: Crowdsensing, crowdsourcing and big data as pillars of industry 4.0. Published in Future Internet **10**, 24 (2018)
Pryss, R., Reichert, M., Langguth, B., Schlee, W.: Mobile crowd sensing services for tinnitus assessment, therapy, and research. In Proc. of IEEE International Conference on Mobile Services, pp. 352– 359, June (2015)
Punjabi, D. M., Tung, L. P., Lin, B. S. P.: CrowdSMILE: A Crowdsourcing-Based Social and Mobile Integrated System for Learning by Exploration. In Proc. of IEEE 10th Int. Conf. Ubiquitous Intell. Comput. 2013 IEEE 10th Int. Conf. Auton. Trust. Comput., pp. 521–526, December (2013)
Puzio, P., Molva, R., Önen, M., Loureiro, S.: Block-level de-duplication with encrypted data. Open J. Cloud Comput. (OJCC) **1**(1), 10–18 (2014)
Qiu, C., Squicciarini, A. C., Carminati, B., Caverlee, J., Khare, D. R.: Crowdselect: Increasing accuracy of crowdsourcing tasks through behavior prediction and user selection. In Proceedings of the 25th ACM International on Conference on Information and

Knowledge Management, ser. CIKM '16. New York, NY, USA: ACM, 2016, pp. 539–548 (2016)
Quinn, A.J., Bederson, B. B.: Human computation: a survey and taxonomy of a growing field. In Proc. of ACM CHI'11. pp. 1403-1412. May. https://doi.org/10.1145/1978942.1979148 (2011)
Rana, R. K., Chou, C.T., Kanhere , S.S., Bulusu, N., Hu, W.: Earphone: an end-to-end participatory urban noise mapping system. In Proc. of the 9th ACM/IEEE International Conference on Information Processing in Sensor Networks (2010)
Reddy, S., Parker, A., Hyman, J., Burke, J., Estrin, D., Hansen, M.: Image browsing, processing, and clustering for participatory sensing: Lessons from a dietsense prototype. In Proceedings of the 4th Workshop on Embedded Networked Sensors, ser. EmNets'07. pp. 13–17, New York, NY, USA: ACM (2007)
Reilly, J., Dashti, S., Ervasti, M., Bray, J.D., Glaser, S.D., Bayen, A.M.: Mobile Phones as Seismologic Sensors: Automating Data Extraction for the iShake System. Proc. IEEE Trans. Autom. Sci. Eng **10**(2), 242–251 (2013)
Ren, J., Zhang, Y., Zhang, K., Shen, X.: SACRM: social aware crowdsourcing with reputation management in mobile sensing. J. Comput. Commun. **65**, 55–65 (2015)
Restuccia, F., Ghosh, N., Bhattacharjee, S., Das, S.K., Melodia, T.: Quality of information in mobile crowdsensing: Survey and research challenges. ACM Trans. Sensor Netw. (TOSN) **13**(4), 1–43 (2017)
Roemer, J., Groman, M., Yang, Z., Wang, Y., Tan, C. C., Mi, N.: Improving virtual machine migration via deduplication. In Proc. of IEEE MASS (2014)
Ruiz Correa, S., Santani, D., Ramirez Salazar, B., Ruiz Correa, I., Rendon Huerta, F.A., Olmos Carrillo, C., Sandoval Mexicano, B.C., Arcos-Garcia, Á.H., Hasimoto-Beltrrn, R., Gatica-Perez, D.: Sensecityvity: Mobile crowdsourcing, urban awareness, and collective action in mexico. Proc. IEEE Pervasive Comput. **16**(2), 44–53 (2017)
Samulowska, M., Chmielewski , S., Raczko, E., Lupa, M., Myszkowska, D., Zagajewski, B.: Crowdsourcing without Data Bias: Building a Quality Assurance System for Air Pollution Symptom Mapping. In international journal of geo-information, volume 10, issue 2 (2021)
Schenk, E., Guittard, C.: Towards a characterization of crowdsourcing practices. J. Innov. Econ. Manag.**7**(1), 93–107 (2012)
Shen, H., Li, Z.: New bandwidth sharing and pricing policies to achieve a win-win situation for cloud provider and tenants. In Proc. Of INFOCOM, 2014 (2014)
Sherchan, W., Jayaraman, P. P., Krishnaswamy, S., Zaslavsky, A., Loke, S., Sinha, A.: Using on-the-move mining for mobile crowdsensing. In Proc. of MDM, pages 115–124 (2012)
Shin, H., Park, T., Kang, S., Lee, B., Song, J., Chon, Y., Cha, H.: Cosmic: Designing a mobile crowd-sourced collaborative application to find a missing child in situ. In Proceedings of the 16th International Conference on Human-computer Interaction with smart devices & Services, ser. MobileHCI '14. New York, NY, USA: ACM, 2014, pp. 389–398 (2014)
Sims, M.H., Fagnano, M., Halterman, J.S., Halterman, M.W.: Provider impressions of the use of a mobile crowdsourcing app in medical practice. Health Inform. J. **22**(2), 221–231 (2016). (**pMID: 25167866**)
Srinivasan, K., Bisson, T., Goodson, G. R., Voruganti, K.: iDedup: latency-aware, inline data deduplication for primary storage. In FAST'12: Proceedings of the 10th USENIX conference on File and Storage Technologies. Vol. 12, pp. 1-14. February (2012)
Staniek, M.: Road pavement condition diagnostics using smartphone-based data crowdsourcing in Smart cities. J. Traffic Transp. Eng. **8**(4), 554–567 (2021)
Tamilin, A., Carreras, I., Ssebaggala, E., Opira, A., Conci, N.: Context-aware mobile crowdsourcing. In Proceedings of the 2012 ACM Conference on Ubiquitous Computing, ser. UbiComp '12. New York, NY, USA: ACM, 2012, pp. 717–720 (2012)
Teodoro, R., Ozturk, P., Naaman, M., Mason, W., Lindqvist, J.: The motivations and experiences of the on-demand mobile workforce. In Proc. of the ACM conference on Computer supported cooperative work (CSCW) (2014)
Thebault Spieker, J., Terveen, L., Hecht, B.: Avoiding the south side and the suburbs: the geography of mobile crowdsourcing markets. In Proc. of the CSCW. pp: 265-275. https://doi.org/10.1145/2675133.2675278 (2015)
To, H., Ghinita, G., Shahabi, C.: A framework for protecting worker location privacy in spatial crowdsourcing. In Proc. VLDB Endow. **7**(10), 919–930 (2014)
Tong, Y., Chen, L., Shahabi, C.: Spatial crowdsourcing: challenges, techniques, and applications. J. ACM Proc. VLDB Endow. **10**, 1988–1991 (2017)
Tu, J., Cheng, P., Chen, L.: Quality-assured synchronized task assignment in crowdsourcing. In computer science databases of Cornell University. arXiv:1806.00637 (2018)
Unbabel - Machine + Crowd Translation you can trust. Available: https://unbabel.com/. Accessed 12 Nov 2019
Victorino, J. N. C., Estuar, M. R. J. E.: Profiling Flood Risk through Crowdsourced Flood Level Reports. In Proc. of Int. Conf. IT Converg. Secur., pp. 1–4, October (2014)
Wang, Y., Cai, Z., Zhan, Z., Gong, Y., Tong, X.: An Optimization and Auction-Based Incentive Mechanism to Maximize Social Welfare for Mobile Crowdsourcing. IEEE Trans. Comput. Soc. Syst. **6**(3), 414–429 (2019). https://doi.org/10.1109/TCSS.2019.2907059
Wang, Z., Huang, Y., Wang, X., Ren, J., Wang, Q., Wu, L.: Social-Recruiter: Dynamic Incentive Mechanism for Mobile Crowdsourcing Worker Recruitment With Social Networks. IEEE Trans. Mobile Comput. **20**(5), 2055–2066 (2021). https://doi.org/10.1109/TMC.2020.2973958
Wang, P., Lin, C., Obaidat, M.S., Yu, Z., Wei, Z., Zhang, Q.: Contact Tracing Incentive for COVID-19 and Other Pandemic Diseases From a Crowdsourcing Perspective. IEEE Internet Things J.l **8**(21), 15863–15874 (2021). https://doi.org/10.1109/JIOT.2020.3049024
Wang, R.Q., Mao, H., Wang, Y., Rae, C., Shaw, W.: Hyper-resolution monitoring of urban flooding with social media and crowdsourcing data. ACM J. Comput. Geosci. **111**, 139–147 (2018)
Wang, J., Wang, Y., Zhang, D., Helal, S.: Energy Saving Techniques in Mobile Crowd Sensing: Current State and Future Opportunities. IEEE Commun. Magaz. **565**, 164–169 (2018)
Wang, L., Zhang, D., Yan, Z., Xiong, H.: effSense: A Novel Mobile Crowd-Sensing Framework for Energy-Efcient and Cost-Effective Data Uploading. Proc. IEEE Trans. Syst. Man, Cybern. Syst. **45**(12), 1549–63 (2015)
Wang, Y., Jia, X., Jin, Q., Ma, J.: Mobile Crowdsourcing: Architecture, Applications, and Challenges . (2015) In proceedings of IEEE 12th Intl Conf on Ubiquitous Intelligence and Computing and IEEE 12th Intl Conf on Autonomic and Trusted Computing and IEEE 15th Intl Conf on Scalable Computing and Communications and Its Associated Workshops (UIC-ATC-ScalCom) (2015)
Wang, Y., Hu, W., Wu, Y., Cao, G.: Smartphoto: A resource-aware crowdsourcing approach for image sensing with smartphones. In Proc.of MOBIHOC, pp. 113–122, Philadelphia, August (2014)
Weinsberg, U., Li, Q., Taft, N., Balachandran, A., Sekar, V., Iannaccone, G., Seshan, S.: Care: Content aware redundancy elimination for challenged networks. In Proc. of Hotnets, Seattle, October (2012)
Wildani, A., Miller, E. L., Rodeh, O.: Hands: A heuristically arranged non-backup in-line deduplication system. In

proceedings of IEEE 29th International Conference on Data Engineering (ICDE). pp. 446-457. April (2013)
Xie, X., Chen, H., Wu, H.: Bargain-Based Stimulation Mechanism for Selfish Mobile Nodes in Participatory Sensing Network. In Proc. 6th Annual IEEE ComSoc Conf. Sensor, Mesh and Ad Hoc Commun. and Networks, pp. 1–9 (2009)
Xiong, H., Zhang, D., Chen, G., Wang, L., Gauthier, V., Barnes, L.E.: iCrowd: Near-Optimal Task Allocation for Piggyback Crowdsensing. Proc. IEEE Trans. Mobile Comput. **15**(8), 2010–22 (2016)
Xu, J., Chen, G., Zhou, Y., Rao, Z., Yang, D., Xie, C.: Incentive Mechanisms for Large-Scale Crowdsourcing Task Diffusion Based on Social Influence. IEEE Trans. Veh. Technol. **70**(4), 3731–3745 (2021). https://doi.org/10.1109/TVT.2021.3063380
Xu, Y., Tang, P., Liu, J.: Resource Scheduling Algorithm based on Multi-target Balance in Enterprise Gloud Storage System. J. Theor. Appl. Inf. Technol. **48**(3), 1578–1583 (2013)
Xu, L., Hao, X., Lane, N. D., Liu, X., Moscibroda, M T.: More with less: Lowering user burden in mobile crowdsourcing through compressive sensing. In Proc. of ACM UbiComp, pages 659–670, Osaka (2015)
Xu, L., Hao, X., Lane, N.D., Liu, X., Moscibroda, T.: 2015. Cost-aware compressive sensing for networked sensing systems, In IPSN (2015)
Yan, T., Kumar, V., Ganesan, D.: Crowdsearch: Exploiting crowds for accurate real-time image search on mobile phones. In Proc. of ACM Int. Conference on MobiSys (2010)
Yang, K., Zhang, K., Ren, J., Shen, X.: Security and privacy in mobile crowdsourcing networks: challenges and opportunities. IEEE Commun. Magaz. **53**(8), 75–81 (2015). https://doi.org/10.1109/MCOM.2015.7180511
Yang, T., Jiang, H., Feng, D., Niu, Z., Zhou, K., Wan, Y.: DEBAR: A scalable high-performance de-duplication storage system for backup and archiving. In Proceedings of the 2010 IEEE International Parallel and Distributed Processing Symposium (IPDPS), pp. 1–12, Atlanta, GA. https://doi.org/10.1109/IPDPS.2010.5470468 (2010)
Yang, C., Cronin, P., Agambaye, A., Ozev, S., Cetin, A. E., Orailoglu, A.: A Crowd-Based Explosive Detection System with Two-Level Feedback Sensor Calibration. In Proceedings of the 39th International Conference on Computer-Aided Design, Article No.: 8, pp 1–9, November (2020)
Yang, D., Xue, G., Fang, X., Tang, J.: Incentive Mechanisms for Crowdsensing: Crowdsourcing with Smartphones. In Proc. of IEEE/ACM Transactions on Networking. 24 , Issue: 3 , 1732-1744, June (2016)
Yang, Y., Sherman, M., Lindqvist, J.: Disaster mitigation by crowdsourcing hazard documentation. In Proc. of IEEE Glob. Humanit. Technol. Conf. (GHTC2014), pp. 93–98, October (2014)
Yi, W. J., Jia, W., Saniie, J.: Mobile Sensor data collector using Android Smartphone. In IEEE 55th International Midwest Symposium on Circuits and System (MWSCAS), pp 956-959 (2012)
Zamora, W., Calafate, C. T., Cano, J., Manzoni, P.: A survey on smartphone-based crowdsensing solutions. J. Mobile Inf. Syst. 2016, Article Id 9681842, pp.26. https://doi.org/10.1155/2016/9681842 (2016)
Zhang, Y., Chen, C.L.P.: Secure Heterogeneous Data Deduplication via Fog-Assisted Mobile Crowdsensing in 5G-Enabled IIoT. IEEE Trans. Ind. Inform. **18**(4), 2849–2857 (2022). https://doi.org/10.1109/TII.2021.3099210
Zhang, J., Sheng, V.S., Li, T., Wu, X.: Improving crowdsourced label quality using noise correction. Proc. IEEE Trans. Neural Netw. Learn Syst. **29**(5), 1675–1688 (2018)
Zhang, B., Liu, C. H., Lu, J., Song, Z., Ren, Z., Ma, J., Wang, W.: Privacy-preserving QoI aware participant coordination for mobile crowdsourcing. In preodicals of Computer Networks. Vol 101, 29–41. June. https://doi.org/10.1016/j.comnet.2015.12.022 (2016)
Zhang, Y., van der Schaar, M.: Reputation based incentive protocols in crowdsourcing applications. In Proc. of IEEE INFOCOM, pp: 2140–2148. https://doi.org/10.1109/INFCOM.2012.6195597 (2012)
Zhang, D., Xiong, H., Wang, L., Chen, G.: Crowdrecruiter: Selecting participants for piggyback crowdsensing under probabilistic coverage constraint. In ACM UbiComp, pages 703–714, Seattle (2014)
Zhao, Y., Han, Q.: Spatial crowdsourcing: current state and future directions. IEEE Commun. Magaz. **54**(7), 102–107 (2016)
Zhao, B., Liu, X., Chen, W.-N., Liang, W., Zhang, X., Deng, R.H.: PRICE: Privacy and Reliability-Aware Real-Time Incentive System for Crowdsensing. IEEE Internet Things J. **8**(24), 17584–17595 (2021). https://doi.org/10.1109/JIOT.2021.3081596
Zhao, B., Tang, S., Liu, X., Zhang, X., Chen, W.-N.: IronM: Privacy-Preserving Reliability Estimation of Heterogeneous Data for Mobile Crowdsensing. IEEE Internet Things J. **7**(6), 5159–5170 (2020). https://doi.org/10.1109/JIOT.2020.2975546
Zheng, Y., Capra, L., Wolfson, O., Yang, H.: Urban computing: Concepts, methodologies, and applications. ACM Trans. On Intelligent Systems and Technology (TIST) 2014; **5**(3), 38 (2014)
Zhou, H., Wang, H., Li, X., Leung, V.C.M.: A survey on mobile data offloading technologies. In Proc. IEEE Access **6**, 5101–5111 (2018)
Zhuang, Z., Kim, K.-H., Singh, J. P.: Improving energy efficiency of location sensing on smartphones. In Proceedings of the 8th International Conference on Mobile Systems, Applications, and Services, ser. MobiSys '10. ACM, pp. 315–330. New York, NY, USA (2010)

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