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A Review of Mobile Crowdsourcing Architectures and Challenges: Toward Crowd-Empowered Internet-of-Things

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ABSTRACT Crowdsourcing using mobile devices, known as mobile crowdsourcing, is a powerful approach incorporating human wisdom into mobile computations to solve problems while exploiting the advantages of mobility and context-awareness. The problems that can be tackled include the use of geographically distributed tasks, and mobile sensing using the collective wisdom of the crowd. However, the implementation of mobile crowdsourcing applications has been found to be challenging to users due to the nature of dynamic sensing, crowd engagement with data distribution, and a process of data verification. In this paper, we provide an extensive survey of the literature on mobile crowdsourcing research, highlighting the aspects of particular concerns in terms of implementation needs during the development, architectures, and key considerations for their development. We present a taxonomy based on the key issues in mobile crowdsourcing and discuss the different approaches applied to these issues. We also provide a critical analysis of some challenges and suggest directions for future work. In particular, with the future Internet-of-Things in view, we generalize the notion of mobile crowdsourcing to thing crowdsourcing, where crowdsourcing can be issued from smart Internet-connected things that need to harness the human resources to solve problems.

INDEX TERMS System architecture, application, mobility, mobile crowdsourcing, Internet-of-Things, smart things.

I. INTRODUCTION

In the past decade, crowdsourcing especially *mobile crowdsourcing* has emerged to facilitate data processing and problem solving. Mobile crowdsourcing refers to a group of people who voluntarily collects and shares data using widely available mobile devices [1]. This data is processed and provided via a data-sharing infrastructure to third parties who are interested in integrating this data. Typically, a mobile crowdsourcing system consists of a platform residing on the cloud and mobile smartphone. Along with the unique multi-sensing capabilities of modern mobile devices, the smartphone can eventually unfold the potential of crowdsourcing. Smartphones offer a great platform for extending either web-based or distributed crowdsourcing applications to a larger contributing crowd and makes contributing easier and omnipresent. Moreover, smartphone users are able to provide large amounts of opportunistic or participatory data that can contribute to complex and novel problem solving. Therefore, the ultimate goal of mobile crowdsourcing is to utilize mobile sensing and humans to collect and analyze the information of people and surrounding environments, and then provide useful information and services to end users [2], [3]. Mobile crowdsourcing platforms in the market such as Waze,[1] Gigwalk[2] and BeMyEye[3] allow users to post tasks that are completed by human workers who receive rewards or payment in return or do so voluntarily. For instance, BeMyEyes[4] apps help blind people who wish to take a picture send a question to volunteer helpers from around the world and then receive an answer back from the crowd in seconds.

However, implementing mobile crowdsourcing applications is still challenging. First, program design with human computation is profoundly different from traditional computer-based systems. It needs powerful new

[1]https://www.waze.com/
[2]http://www.gigwalk.com/
[3]https://www.bemyeye.com/
[4]https://www.bemyeyes.com/

programming metaphors and infrastructures that support the design, implementation, and automated execution of human computations. Second, since the systems rely on humans, the process might take longer than before in order to find responding workers and collect the completed tasks. Therefore, recruitment and motivation techniques under a limited budget are an essential component of developing crowdsourcing systems. Third, the process of accumulating the crowds' feedback needs to involve verification. Developing effective algorithms to leverage decision making, average the guess of a group of people, even to avoid a systemic bias about the answer, are substantial challenges. Hence, developers have to manage tradeoffs between speed, money, and reliability in designing their algorithms.

In view of these challenges, this paper first reviews the existing mobile crowdsourcing literature based on a survey of significant projects which integrate the ability of mobile sensing to delegate work or computation to humans. We review background knowledge on the mobile crowdsourcing paradigm, highlighting a range of representative mobile platforms for crowdsourcing. We also provide a taxonomy of the issues found in this area and several dimensions and approaches along which these issues have been tackled, focusing on the characteristics of applications and system architectures. We also outline a range of frameworks, techniques, key aspects and challenges for developing mobile crowdsourcing applications. Finally, we expand each dimension to highlight the unique set of challenges in terms of implementation needs in order to be considered during the development and evaluation of such collaborative systems. We also then discuss future work in mobile crowdsourcing and the generalisation from mobile crowdsourcing to thing crowdsourcing.

II. KEY ASPECTS OF MOBILE CROWDSOURCING APPLICATIONS

Mobile crowdsourcing can be utilized for different applications for both scientific and business purposes. In several previous studies, the applications of mobile crowdsourcing have been focused and remarkably classified into the literature surveys. They have proposed the typology of mobile crowdsourcing applications in different aspects. Typical application areas include environment monitoring [4], [5], disaster management [6]–[8], infrastructure monitoring [9], [10], community healthcare [11], [12], transportation, ride sharing and urban sensing [13]–[16], social issues [6], [8], [17] and others [18]–[20]. In the earlier study, mobile crowdsourcing can be categorized as participatory and opportunistic based on the involvement of participants in sensing actions [21]. Later, many researchers attempted to explore the applications of mobile crowdsourcing/sensing based on different purposes and from various aspects.

Among those, Ganti *et al.* [22], focusing on phenomenon being measured and mapped, classify mobile crowdsourcing applications into three categories (a) environmental, (b) infrastructure, and (c) social. Feng *et al.* [23] identifies mobile crowdsourcing applications based on the properties of a crowdsourcing task and human assistance including 1) mobile crowd computing, 2) mobile crowdsensing, and 3) human-assisted crowdsourcing. In mobile crowd computing, the applications can outsource a computing task to mobile devices and then collect their computing results via various networks. While in mobile crowdsensing, the applications utilize mobile devices as sensors to collect information about environments, infrastructures, and mobile users, human-assisted crowdsourcing aims to utilize human intelligence to finish a certain task.

The study in [24] classified mobile crowdsensing applications into three categories namely group, community, and urban sensing. According to the key characteristics of mobile crowdsourcing as mentioned in [1], the applications can be categorized as either people-centric or environment-centric. People-centric applications collect data about the user (e.g., physical effort, sport experiences etc.) whereas environment-centric applications capture information about the surroundings of the user (i.e., air quality, noise pollution, road condition, damages, disasters etc.).

In this review, we explore mobile crowdsourcing applications with regards to four key aspects. Yufeng *et al.* [25] and Wang *et al.* [26] study on the building blocks of mobile crowdsourcing systems. As they mentioned, the crowdsourcing system needs to address a number of fundamental challenges including quality control, task management, incentives, as well as security and privacy. Furthermore, Geiger *et al.* [27] design four basic questions that are important for building the crowdsourcing application: "What is being done?", "Who is doing it?", "Why are they doing it?", and "How is it being done?". From this point, we analyze the mobile crowdsourcing applications along four dimensions: 1) Tasks, 2) Participations, 3) Data Collection, and 4) Processing. Fig. 1 summarizes the four aspects of mobile crowdsourcing applications we examine in this paper.

A. TASK

A task in mobile crowdsourcing applications typically refers to a human intelligence required task (which could be aided by machine computations) that employs mobiles and human sensors to collect user data. we can classify the characteristics of crowd tasks into many distinct dimensions as follows.

1) TASK TYPES

Tasks can be divided into two types that could be either *human-companion device tasks* or *human intelligence tasks*. The human-companion device tasks utilize mobile devices as sensors to collect human observation and information about environment and infrastructures. Such devices could be smartphones, smart vehicles, wearable devices, and so on that may own several electronic sensors by default (accelerometers, camera, microphone or thermometer). These kinds of tasks are widely applied in personal data collection [11], [12], e.g., personal health data, sport experiences, and in

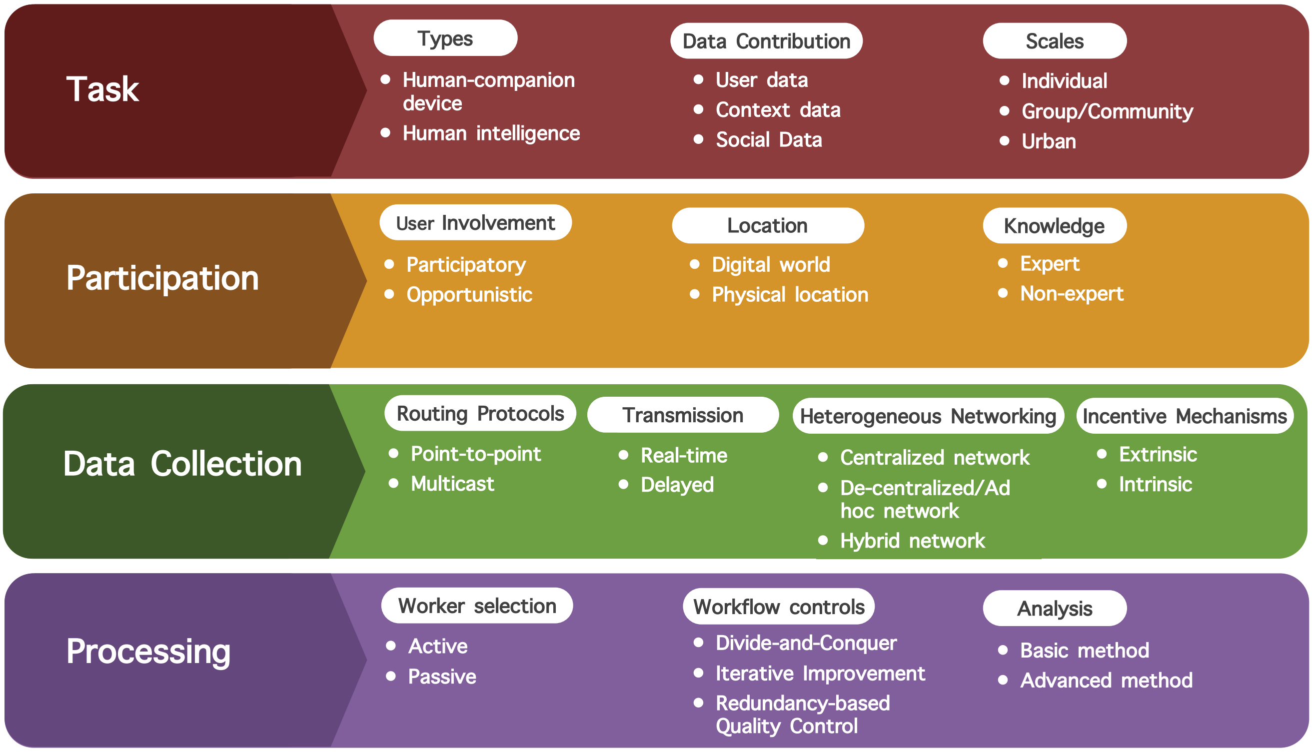

FIGURE 1. **Four key aspects of mobile crowdsourcing applications.**

environment monitoring [4]–[6], [13], e.g., noise, weather and pollution. On the other hand, human intelligence tasks utilize human wisdom to perform tasks that are hard for computers to do but trivial for humans. Examples of such tasks [15], [16] are related to the areas of sentiment analysis, natural language understanding, image recognition and creativity. The solutions on these tasks can be subjective due to different understandings and experiences.

2) DATA CONTRIBUTION

The aim of mobile crowdsourcing systems is to extract crowd intelligence from a large volume of user contributed data generated by their mobile devices. Based on the value of intelligence, we classify it into three main categories including user, context, and social data.

- **User data** refers to the extraction of personal contexts (e.g., location, physical activity), health vitals (e.g. heart rate, blood pressure and sugar level) and behavioral patterns (e.g., mobility patterns, daily life patterns).
- **Context data** regards to information about the surroundings of the users or their status (e.g., noise level of a bus stop, traffic dynamics of a street) or the semantics (the logical type) of a particular area. The area can be small (e.g., a restaurant) or large (e.g., an urban area).
- **Social data** refers to user-generated data in mobile social networks which bridge the gap between online interaction and physical elements (e.g., check-in places). The data collected from social network is able to provide another way to understand urban dynamics. Moreover, social data is about the contexts of a group or a community, such as social activity type, interpersonal relations, infer group activities and so on [28].

3) SCALES

The scale of crowds in which workers are involved can be small or large, ranging from a person to a group/community to city scale.

- **Individual** refers to the number of available individuals to implement crowdsourcing (possibly in the context of sharing economies) by conducting activities such as performing a task or providing a service. Recently, there is an emerging of a new paradigm called the *sharing economy*, referring to a highly flexible economic network that allows people to share resources such as equipment, services, and skills with one another. For example, via a platform, after a task requester submits tasks with some information (e.g., location, time) to the server, only a potential worker is selected to complete the tasks and send data to the server. One can consider UberEats[5] as a ride-sharing platform that aims to improve the food delivery service. Users could request food delivery from any restaurant on the service platform. The platform will then assign delivery tasks to nearby workers for picking up food packages from relevant restaurants.

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

- **Group/Community** occurs when the participants share information gathered from personal sensing activities with friends of a social group or community. The participants come from a strongly bonded group or community, with established social ties and trust among members [24]. They also are connected intermittently when they opportunistically contact each other (e.g., spatially nearby phones). For example, GroupMe, proposed in [29] is a giant stride in this direction to help facilitate the discovery of groups within mobile crowdsourcing systems.
- **Urban** could involve geographically broader ranged crowdsourcing tasks, targeting participants at city scale to collect multi-modal data streams from the surrounding environment. The data contributed from a large number of participants can be combined to create a spatio-temporal view of the phenomenon of interest and also to extract important community statistics [30]. Typical application areas include urban traffic [31], public safety/security related data [6]–[8] and environmental monitoring [4], [5].

B. PARTICIPATION

Geiger *et al.* [27] state that the nature of the participants in a crowdsourcing system correlates with the characteristics of the tasks performed. The role and nature of its crowd participants can differ substantially. Mobile crowdsourcing applications can be decomposed according to the capability of the required participants in the following aspects.

1) USER INVOLVEMENT

Based on the involvement of participants in sensing actions, mobile crowdsourcing can be categorized as: opportunistic and participatory [22].

Opportunistic crowdsourcing is more autonomous, and user involvement is minimal and the mobile device itself makes decisions according to the sensed and stored data e.g., continuous location sampling without the explicit action of the user. A typical example of opportunistic crowdsourcing is DeepEar [32], an application that opportunistically captures the level of sound from smartphones in order to, through deep learning methods, classify sounds into ambient noise, speech or music. Moreover, Panichpapiboon and Leakkaw [31] used the accelerometer only to estimate the vehicle's speed and traffic density, assuming an inverse relationship between density and speed.

In participatory sensing, the active involvement of individuals to contribute sensor data (e.g., taking a picture, reporting a road closure, sentiment analysis) is required. Moreover, with the rapid development of mobile internet, mobile social network services like Facebook and Twitter are as another participatory sensing mode to form a collective intelligence through analyzing and integrating the perception data from a large crowd. Consequently, participatory sensing can leverage human intelligence by enabling users to transparently contribute to complex and novel problem solving. This type of mobile crowdsourcing applications, such as Transafe [15], SenseCityVity [16], IncentMe [33], CoSMiC [19] and CrowdFound [20], requires human abilities, specializations, or skills of participants.

2) LOCATION-AWARENESS

With the ubiquity of interactive mobile devices providing location awareness and network connectivity, every person with a smartphone can act as a sensor collecting and sharing various types of spatio-temporal data instantaneously. Crowd workers exploit multi-mobile sensors such as accelerometers, gyroscopes, GPS, cameras and microphones to publish locations, photos, messages and voices via mobile crowdsourcing applications or social media sites. Typically, these activities do not require the workers' real-time location information. They are able to publish their work offline at anytime. Different from traditional mobile crowdsourcing, workers are required to perform a set of tasks by physically travelling to certain locations at particular times called spatial crowdsourcing. This paradigm is exploited in numerous industries, e.g. Uber,[6] TaskRabbit,[7] Waze, Gigwalk, etc., and has applications in numerous domains such as citizen journalism, tourism, intelligence, disaster response and urban planning.

3) KNOWLEDGE

Crowd participants are grouped depending on the complexity and skills involved in the tasks. We can distinguish participants as general and specific purpose as well. Mobile crowdsourcing applications may require a non-expert or a moderate education for participants to complete the tasks. They also require expertise and substantial knowledge in a particular domain to do the tasks. For example, an image-tagging task or ranking products does not require much specialized expertise to perform, which means almost anyone can do the task. On the other hand, the applications, such as DocCHIRP [34], CrowdHelp [35], involve diagnosis of unusual cases; hence, such crowd applications requires specific abilities, specializations, or skills on the part of participants.

C. DATA COLLECTION

Traditional methods of data management in crowdsourcing generally considered only centralized or client-server communication while mobile ad-hoc network communication involves multi-hop transfers and decentralized processing. A node disseminates tasks among crowd workers through mobile peers in its range, obtains responses from such mobile devices, and integrates the responses to obtain real-time answers. We define the key techniques related to data collection in mobile crowdsourcing applications which consist of four distinct dimensions: routing protocol, transmission, heterogenous networking, and incentive mechanism.

[6]https://www.uber.com/
[7]https://www.taskrabbit.com/

1) ROUTING PROTOCOLS

Routing protocol refers to the propagation strategy to disseminate crowd tasks among peers, then it becomes significant for data transmission in mobile crowdsourcing systems. Mobile users can easily interact with each other in a mobile network fashion which can be regarded as an ad-hoc network supporting multi-hop routing, content forwarding, and distributed decentralized processing. We categorize the task propagation of crowdsourcing in opportunistic networks into two aspects: point-to-point, multicast communication [36]. Firstly, point-to-point connection refers to a communication between two nodes or endpoints. Based on this connection, a node can only communicate or transmit information to one node at a time. In a mobile ad hoc network, the standard wireless link technology, such as Bluetooth, can also support point-to-point communication which follows the master-slave relationship. In contrast, the multicast connection is accomplished through one-to-many concurrent connections. In mobile ad hoc networks, the standard wireless communication technology such as traditional wifi infrastructure networks, wifi direct, LTE direct also supports this kind of connections.

2) TRANSMISSION

Crowdsourced data from workers would be shipped to the backend server. Data can be transmitted in real time (e.g., via mobile networks) or with a delay (e.g., when WLAN is available). In real time situations, data is collected locally from workers then deliver and interpret it in real time e.g., real-time traffic information, air quality at different places, etc. In offline situations, delayed transmission may be essential to meet quality and security requirements. In such a case, data transmission would start manually when a connection to the Internet is available (e.g., via WLAN).

3) HETEROGENEOUS NETWORKING

By leveraging ubiquitous and heterogeneous network capabilities, mobile crowdsourcing has huge potential for growth in business and industrial sectors. It is able to provide transient network connections and effective collection of mobile crowdsourcing data. Enhancement of current mobile devices has been apparent with a provision of multiple wireless communication interfaces and supported via different wireless technologies. Examples include a smartphone equipped with GSM/4G/5G, WiFi, and Bluetooth interfaces. The GSM/4G/5G and WiFi interfaces facilitate network connectivity with communication infrastructure that exists in the areas (e.g., via cellular base stations in a city or WiFi access points in a work building). Meanwhile, connections over relatively large areas can be made possible through the tools such as Bluetooth, ZigBee or WiFi Direct that provide short-range connection among mobile devices themselves and form self-organized opportunistic networks for data distributing and sharing [37]. Therefore, interconnecting heterogeneous network elements and exchange data efficiently raise important research challenges and enriched opportunities for mobile crowdsourcing applications.

However, the sensing environment of this platform includes multiple sources and heterogeneous information from mobile workers. While different mobile crowdsourcing applications may have various connection architectures and communication requirements. It can operate in two different data processing methods. The centralized method transmits all gathered data to a cloud server for processing, whereas the decentralized method is where all computations and communications are performed locally by peers (mobile devices) in an appropriate manner. Recently, cloud computing is widely used for analyzing crowdsourced data especially for crowdsourcing IoT data [38], [39]. However, crowdsourcing data are often analyzed in a cloud platform where latency will be quite high. It is not suitable for real-time events such as disaster and natural calamities management that require an immediate action by the public safety authorities [40].

Nevertheless, one possible solution to such a limitation is the exploitation of edge computing or fog computing [41], [42]. By fog computing, the most time-sensitive data at the network edge, close to where it is generated, can be analyzed. It also works on crowdsourced IoT data for milliseconds response-time applications and delivers the selected data to the cloud for historical analysis and longer-term storage for future use [42], [43].

4) INCENTIVE MECHANISMS

The motivation or incentive is a critical factor to encourage participation in mobile crowdsourcing applications. An incentive scheme is a crucial part of a recruitment strategy which requires users to contribute to or perform crowd tasks in mobile crowdsourcing systems [44].

Doan *et al.* [45] discussed crowdsourcing systems on the Web from a variety of perspectives. They introduce the nature of collaboration for crowd contribution in two aspects: explicitly allowing contributors to build artifacts that are beneficial to the whole community and implicitly permitting contributors to solve a problem as a side effect of something else they are doing. They also define the recruitment strategies in five major aspects including using authority, paying users, asking for volunteers, making contributions a requirement to use a different service, and piggybacking on established systems.

Kaufmann *et al.* [46] explore the workers' motivations in crowdsourcing. According to their study, the motivating factors are categorized into intrinsic (e.g., enjoyment and community motivation) and extrinsic motivation (immediate payoffs, delayed payoffs, social motivation). They found that the extrinsic motivational categories have a strong effect on the time spent on crowdsourcing platforms; also, intrinsic motivation aspects are important, especially the different facets of enjoyment-based motivation. Similar to the study of [45], [46], we simplified the incentive aspects of mobile crowdsourcing into two dimensions: implicit and explicit motivations. The explicit motivations relate to activities including payment, financial reward, and social obligation which impact upon contributors to participate in the tasks. On the other hand, the implicit motivations are based on the satisfaction associated with the activity itself such as passion, enjoyment, community identification, or personal achievement. The explicit examples are the financial rewards of micro-tasks, such as MicroMobile [47], OpenStreetMap,[8] Gigwalk or BeMyEye.[9] In implicit purpose, the examples are ESP game [48], reCAPTCHA,[10] Waze, EyeSpy.[11]

D. PROCESSING

In general, mobile crowdsourcing applications exploit wireless sensing networks to sense, transmit, and process data and crowdsourcing tasks. The data of these systems is processed and provided via a data-sharing infrastructure to third parties who are interested in integrating this data. Typically, a mobile crowdsourcing system consists of a platform residing on the cloud and mobile devices. We decompose the processing of mobile crowdsourcing into three aspects: 1) worker selection, 2) workflow controls, and 3) analysis.

1) WORKER SELECTION

In mobile crowdsourcing, worker selection aims to allocate a specific set of crowdsourced tasks to a set of crowd workers who can potentially finish these tasks more accurately and efficiently - one can also distinguished between active and passive workers. In case of an active worker selected tasks, the participant is actively involved in the process. With the emerging spatial crowdsourcing paradigm, workers can perform a set of spatial tasks (i.e., tasks related to a geographical location and time) posted by a requester. Therefore, this platform needs available workers who can accept and complete the tasks at particular places and times, as required. For instance, Postmates,[12] a company offering on demand food and delivery, is available all around the US. In addition, Uber, Grab[13] and Lyft[14] are success platforms of crowdsourced taxi services that match the tasks with the workers' availabilities, and allocates workers to tasks considering the spatio-temporal requirements.

In case of a passive participation, workers do not have to become active. The data capturing application (with user permission) can run on his/her mobile device in the background which then collect and transmit data automatically. Moreover, workers can passively wait for the platform to assign tasks. The selected workers in passive mode is based on offline statistics collection such as worker contexts and workers' historical task completion performance [49].

2) WORKFLOW CONTROLS

Workflow control of mobile crowdsourcing refers to the process of planning and executing the crowd tasks that can be accurately solved by a pool of crowd workers. Such workflows may decompose larger tasks into smaller subtasks, and later compose subtask solutions into an overall work product. In the literature, they serve as basic building blocks for crowdsourcing algorithms, which can be generally classified into three main patterns as follows.

- **Divide-and-Conquer** algorithms for distributed human computation consist of decomposing, solving and recomposing [50]. It refers to the process of decomposing a problem into sub-problems and composing solutions of sub-problems into a solution. For example, Bernstein *et al.* [51] establish a workflow pattern for proofreading and editing text into three stages called Find-Fix-Verify. Rather than asking a single crowd worker to read and edit an entire paragraph, which might result in poor quality work, this procedure recruits a group of workers to find candidate areas for improvement, then revise a set of candidate improvements, and finally filters out incorrect candidates. The Find-Fix-Verify process divides a task in a manner that maintains accuracy and reliability.
- **Iterative Improvement** is a workflow control that improve the quality of results for refining tasks, such as writing or collective brainstorming at using multiple workers to build on and improve upon an existing task. The iterative improvement design pattern was first described by [52]. They introduced TurKit as a toolkit for deploying iterative tasks to Mechanical Turk.
- **Redundancy-based Quality Control** is a workflow control to ensure the quality of crowdsourcing results. Consider the following example: a requester intends to describe photos by tagging them with meaningful and descriptive keywords in order to categorize these photos in a library. Each photo is assigned to a worker with the proper skills necessary to complete it. However, by asking a sufficient number of workers to perform the same task independently, we are able to gain the most common responses as the solution and expect a high quality of the correct (i.e., majority) answer.

  Barowy *et al.* [53] optimize the majority voting approach by introducing an algorithm to estimate the confidence level of the responses that would be acceptable by the requester. Liu *et al.* [54] studied improvements using a quality control mechanism relying on workers' past performances. Given the probability distribution of workers' performances, they apply the Bayesian theorem to estimate the accuracy of each result.

3) ANALYSIS

Analysis plays a vital role in providing feedback to the requester in order to increase quality as well as in selecting the best result from a large set of crowd solutions. In the existing literature, we can identify two main techniques for analysis data from crowd including basic and advanced approaches. Along the general method, our work focuses on assigning a task to multiple users who submit their individual results

[8]http://www.openstreetmap.org
[9]http://www.bemyeye.com
[10]http://www.google.com/recaptcha
[11]http://www.eyespy.com
[12]https://postmates.com/
[13]https://www.grab.com/
[14]https://www.lyft.com/

to cloud servers and then select the result that is most commonly returned. Other typical examples are majority voting for the product of interest, majority rating/decision and integration aggregation. Schenk and Guittard [55] noted the fundamental distinctions in aggregation processes for crowdsourcing, including integrative and selective methods. *Integrative crowdsourcing* creates value by pooling potentially large quantities of complementary input whereas *selective crowdsourcing* generates value by asking the crowd to provide a set of options.

Conversely, the advanced analysis approach applies various data processing techniques such as machine learning, data mining and other sophisticated algorithms (e.g., Expectation Maximization) to gain insights in crowdsourced data. Advanced data mining and machine-learning algorithms enable automatic knowledge discovery and event/society understanding. However, in order to maximize the benefits of crowdsourced data, it must be taken to prepare the data for processing and the right data mining approach needs to be considered for the specific problem at hand [56]. Today, mobile crowdsourcing enables the collection of huge amounts of data gathered by multiple sources. These sources produce wide ranges of data both structured and unstructured, from historical to real-time, coming from the most diverse sources, e.g., sensors, machines, products, workers, and customers. Hence, big data, playing a key role as an advanced analysis technique is used to compare and interpolate data collected from sensors with related information that is made available on the cloud, so that more efficient and complete solutions can be obtained [57]. Recently, many researchers attempted to explore big data analysis techniques for mobile crowdsourcing based on different purposes and from different perspectives [57]–[59].

III. CROWDSOURCING ARCHITECTURES

In the past decade, numerous mobile crowdsourcing applications have shown potential for business and society. Fuchs-Kittowski and Faust [1] reviewed related conceptual work in the domain of mobile crowdsourcing systems and proposed a general architecture for mobile crowdsourcing applications. The proposed architecture is divided into two parts participants/client and backend-system/server. On the client side, mobile devices contribute to the geo-crowdsourcing campaign by capturing and sharing geospatial data using their own mobile devices. The client provides functions as data capturing and a user interface. The backend system or server performs data storage, processing, and visualization efforts as well as recruit and interacts with well-suited participants.

Ren *et al.* [2] studied mobile crowdsourcing architectures in existing applications. They described two kinds of mobile crowdsourcing models. The first model is an Internet-based scenario where mobile users can potentially be a service provider in the Internet-based mobile crowdsourcing, while the second model is a local-based scenario where mobile users in the vicinity can provide cloud services in local-based mobile crowdsourcing.

Moreover, there are a number of general architectures proposed on mobile crowdsourcing applications like Medusa [60], Vita [61], MoCoMapps [62], PRISM [63], and AnonySense [64]. Those frameworks not only enhance the general architectures to solve cost-efficient development issues but also focus on generality, security, scalability and privacy. Most mobile crowdsourcing applications have been built on Web technologies, allowing online workers to complete the task via the mobile Internet. These main components are generally organized as client-server architectures.

While the above studies use general architectures focusing either on more refined functions of certain subsystems such as data capture, data processing, campaign management or non-functional aspects such as privacy and security, Zhao and Zhu [65] emphasized functional components with the notion of the transformation process - a process or collection of processes that transforms inputs into outputs. There are three categories of components: assigners who initiate and manage the task, providers who respond to the task and attempt to submit their solutions as feedback, and an intermediation platform which links assigners and providers and serves as a crowdsourcing enabler. In addition, Estrin [66] and Khorashadi *et al.* [67] present common architectural components with a particular focus on data capturing and leveraged processing.

Hetmank [68] presents the typical components and functions that may be implemented in crowdsourcing systems with a special focus on campaign management. The author derives four components: user management, task management, contribution management, and workflow management. The crowdsourcing theoretical framework presented by Ponciano *et al.* [69] pays special attention to analyzing strategies for designing and managing distributed applications through crowdsourcing platforms. Their framework is designed to assist the analysis of the diverse processes related to crowdsourcing applications. It is divided into three dimensions: QoS requirements which are requesters' effectiveness measures, design and management strategies related to how platforms manage application execution, and human aspects which are worker characteristics.

Several architectures of applications emphasize task management, e.g. aggregating results obtained from different crowd workers, the distribution of data capturing tasks to participants. Luz *et al.* [70] study crowdsourcing platforms with a focus on solving micro-tasks and complex tasks. They group the crowd tasks into several subtasks such as partition task, aggregation task, qualification task, and grading task. By proposing a task-oriented crowdsourcing system, such tasks connects the worker, the requester, and the systems itself. They attempt to generalize the task flow process as well as analyze the conceptual model through several existing crowdsourcing platforms. Difallah *et al.* [71] propose a framework driven by crowd tasks. The tasks are done by the most suitable worker. Based on push technology, workers and tasks are automatically matched using an underlying categorization structure that exploits entities extracted from the task descriptions as well as deploys the worker profiles based on information available on social networks.

From our analysis of existing mobile crowdsourcing applications and architectures, we present a classification scheme and general architectures with the typical roles, components and functionalities of mobile crowdsourcing systems from the perspective of programmers and practitioners. The main goal of this section is to provide a better understanding of typical functionalities and design aspects during development and evaluation of mobile crowdsourcing systems via generalised architectures. Based on our analysis, we provide generalised centralized and decentralized mobile crowdsourcing architectures. The centralized architecture refers to all gathered data processing at the cloud server, whereas the decentralized architecture is where all computations and communications are performed locally by peers. We describe the details in the following subsections.

A. A GENERALISED CENTRALIZED MOBILE CROWDSOURCING ARCHITECTURE

Mobile crowdsourcing systems have been implemented typically using web-based and client-server communications that are able to provide access via either conventional smartphones or workstations. This architecture is generally a client-server model; that is, the server component provides services, functions and resources to one or many clients that initiate requests for such services. In this model, all computing is done at a central location/server and computing resources reside at the primary data center. The clients or terminals only send requests to the center and then receive the results from their server/cloud services. Fig. 2 illustrates the architecture of a generalised centralized mobile crowdsourcing solution, divided into four layers: Mobile sensing and gathering layer, Connectivity and network layer, Crowd processing layer and End-user layer.

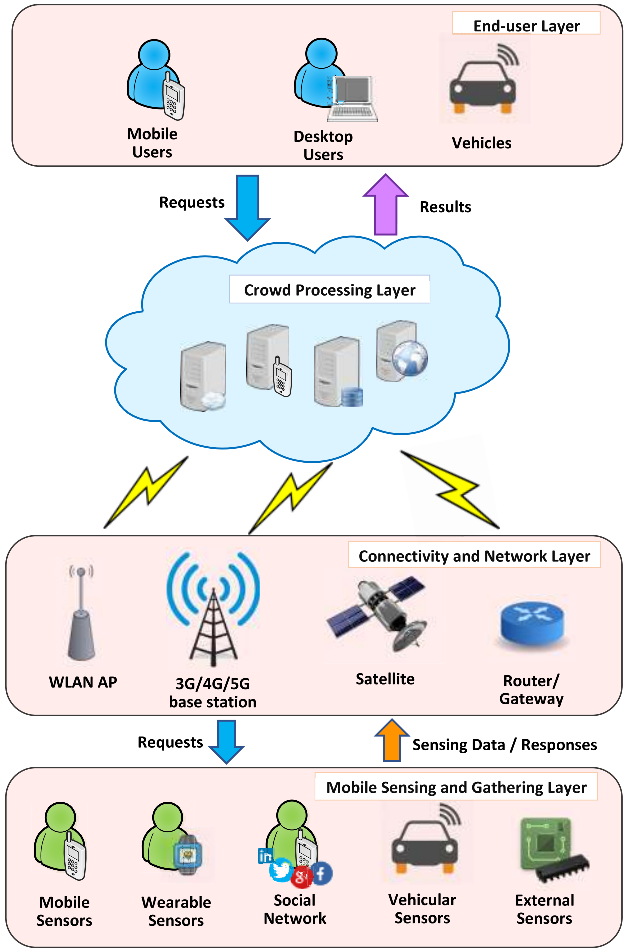

FIGURE 2. Architectural components and roles of centralized crowdsourcing applications.

1) MOBILE SENSING AND GATHERING LAYER

The main role of this layer is to generate and forward the crowd sensing data or crowdsourcing tasks to the main server via wireless communication networks. It contains various sensing devices based on the power of user devices including mobile phones, wearable devices, smart vehicles and so on. These ubiquitous devices allow participants to collect crowd data/tasks from the surrounding environment, e.g. location, movement, ambient context, and health monitoring data. These sensing tasks can be both opportunistic and participatory data [22]. For opportunistic sensing, the data can be triggered automatically (either periodically or based on events) by sensing devices. Participatory sensing can be used to retrieve information about the environment, weather, urban mobility, congestion as well as any other sensory information that collectively forms knowledge [3], [72]. Therefore, fusing machine (mobile devices) and human intelligence have encouraged more informed choices and better decisions using crowd intelligence.

With involving multiple devices, heterogeneous data sources and a large amount of data, mobile crowdsourcing applications have several challenges such as data integration, interoperability, device detection and data sharing [73], [74]. Some efforts in existing research propose semantic approaches to data integration and creating the standards for metadata schema associated with the heterogeneity of data sources. In [75]–[77], they make integration of a formal ontology with an implicit one reflected in a database schema or in a communication protocol specification to retrieve information from different data sources and provide cross-domain crowdsourcing platforms. For such heterogeneous data sources produced by both human and devices, another solution is to have a middleware platform for facilitating collaboration and information exchange. For instance, the middleware is able to abstract the hardware and provide an Application Programming Interface (API) for communication, data management, computation, security, and privacy [78]. Some examples proposing middleware solutions available for mobile crowdsourcing platforms are MobIoT [79] and CUPUS [80].

2) CONNECTIVITY AND NETWORK LAYER

An essential role of this layer is to supply network connectivity to mobile crowdsourcing systems. There are various communication networks in mobile crowdsourcing such as wireless sensor networks, cellular networks (3G/4G/5G), local/public Wi-Fi, Bluetooth, and vehicular ad hoc networks (VANETs). Data collected by mobile sensors is transferred to the server/cloud using these technologies. The primary concerns of this layer are to establish network links and to provide the basic device discovery mechanisms required for context-awareness. These activities could be costly because of service charges (e.g. data plans, data services) and resource consumption (e.g. battery, memory) [2], [37]. Although incentive mechanisms are proposed to provide participants with agreed rewards, it seems that these rewards may not be sufficient if users are to be responsible for extra expenses on network connectivity or have to use their own resources.

There are some research studies to explore techniques to enhance throughput for mobile devices suffering from low cellular data rates [81]–[83]. In [84]–[88], the solutions have been proposed for mobile devices to cooperatively disseminate data. For example, in [84], [85] is proposed a middleware framework that allows mobile users with residue capacity in their data plans to share their access with other nearby mobile users for a small fee. In other examples in [86]–[88], nearby mobile devices cooperate to stream over cellular networks and relay the received data to other mobile phones over Wi-Fi and peer-to-peer networks. Moreover, several challenging security and privacy concerns are raised in mobile crowdsourcing networks [2], [23], [37], [89]. For example, mechanisms are required to protect a users' data when passing through untrusted nodes [84]. And some sensed data may contain location information, which may implicitly reveal a mobile user's movement [90].

3) CROWD PROCESSING LAYER

This layer analyzes, processes, virtualizes and stores crowd tasks and sensor data from the lower layer. Recently, cloud computing has been widely recognized as the next generation computing infrastructure. With a naturally centralized paradigm, cloud computing is currently used for analyzing crowdsourced data and IoT platforms. Processing resources and storage reside at the primary data center. All crowdsourced data collected by mobile devices is uploaded and analyzed in a cloud platform through wireless networks. Cloud computing offers great benefits for mobile crowdsourcing platforms by extending battery lifetime, improving data storage capacity, enhancing processing power, and improving reliability [91]. Although it provides many advantages, cloud computing still creates challenges for latency sensitive mobile crowdsourcing applications such as real-time processing and high degree of mobility. In recent years, fog computing is a new platform extending the cloud computing paradigm to the edge of the networks. Fog computing aim to solve this problem by keeping data at the network edge with local devices (e.g., smartphone, vehicles), rather than routing everything through a central control center [40].

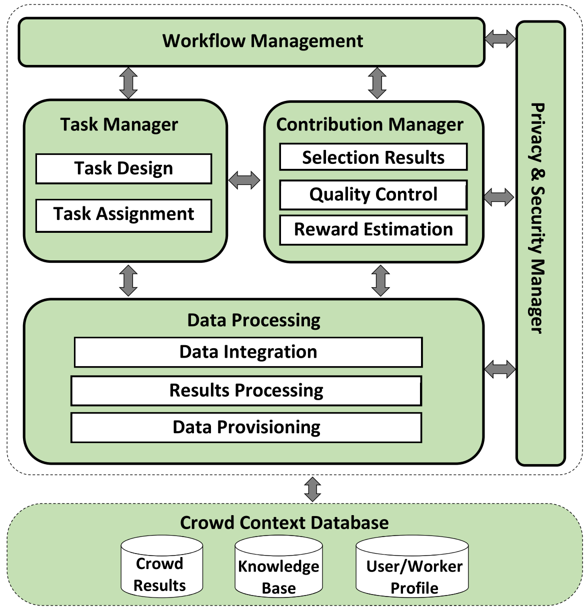

FIGURE 3. The components of crowd processing layer.

Focusing on the crowd processing layer in Fig. 3, we illustrate a generic crowd processing module which can be adapted to the different mobile crowdsourcing architectures in the literature. There are six components connected to each other through a data transmission network: 1) task manager, 2) contribution manager, 3) data processing, 4) workflow management, 5) privacy and security manager and 6) crowd context database. We proceed to detail each of the components.

- **Task Manager**: This component handles the incoming submissions of tasks from requesters and also organizes the distribution of sensing tasks from the service requesters to the service providers.

  On task design, this sub-component dynamically creates tasks as many as required from the requesters via a graphical user interface. The quality of the results highly depends on the task design [39], [89], so that the key aspects of tasks such as, types of tasks, the process of executing tasks, the correspondence of instructions and constraints must be determined before assigning tasks to the crowd. Apart from that, other components, such as keywords, candidate answers, maximum accepted answers, expected reward, distance to the target locations, submission time and latency should be carefully defined. In the task assignment component, the crowdsourcing system should be concerned with assigning the right task to the right workers. For instant, Peng *et al.* [92] proposes CrowdService, an approach based on genetic algorithms, that can synthesize near-optimal cost and time constraints for each crowd service and select a near-optimal set of workers to execute crowd tasks. Qiu *et al.* [93] proposed an approach for the task assignment problem, which offers a theoretically proven algorithm to assign workers to tasks in a cost efficient manner while ensuring high accuracy of the overall task. Moreover, the task would be routed based on the task specification and the worker profile as mentioned in [34] and [94]. Hetmank [68] mentions that the important conditions when assigning the task to the crowd are the sufficient worker's knowledge and skills to complete the task and the appropriate period of time when the worker can and is willing to work.

- **Contribution Manager**: This component is involved in the process of selecting and assembling the solutions from the crowd, for quality assurance as well as for computing appropriate rewards for the crowd. To select the best feedback from a large group of people, several methods such as majority voting, control group or expert decisions have been used [95]–[98].

  Furthermore, various data processing techniques, such as data mining or machine learning algorithms, may be applied to select and combine the results that are often overwhelming and comprise redundant data. For example, Mobasheri *et al.* [13] apply data mining techniques to extract the geometry of sidewalk path segments and to construct sidewalk networks using multiple GPS traces. As another example, the study in [6] exploits Natural Language Processing and Computer Vision techniques to extract hyper-resolution data (text messages from social media and photos from crowdsourcing platforms) with a wide coverage to support urban flooding events. However, to achieve high performance of these techniques, data quality and reliability are needed by crowd workers.

  The next sub component is quality control process that is one of the key aspects to ensure that the quality of feedback from the workers. According to [99], the authors classify the evaluation mechanisms into three levels including no assessment, self-assessment and external assessment. They also found that online workers produce better results when they self-assessed or received external feedback. Moreover, this component deals with the monetary reward to the crowd in the case of paid crowdsourcing platforms. In this method, the system issues monetary rewards by evaluating the quality of work. The approaches such as majority agreement [100]–[102] and a set of known answers to check for errors and to identify workers who make many mistakes [71], [103]–[105] have been used for this component.

- **Data Processing**: The data processing component involves preparing captured data to storage, processing stored data and then arranging data for presentation. From Fig. 3, this component consists of three sub components 1) data integration, 2) results processing, and 3) data provisioning. First of all, the data integration component extracts and transforms captured data from a large group of crowds into internal data structure. For example, each vote is counted and stored in the conventional database. Another example, audio files are analyzed by extracting words for speech recognition or matching with original sounds.

  Meanwhile, the results processing component operates the stored raw data to extract features of interest and get insight into the observed phenomenon. There could be several approaches for data processing such as processing for numeric and statistical modelling, image processing and sophisticated machine learning algorithms [4], [106], [107], depending on the actual application. In the last component, the presented data can be visualizations of the raw data or the processed data for end users. Furthermore, the results are usually presented through web-based applications or on mobile device apps.

- **Workflow Management**: This component manages a workflow designed for complex tasks with requirements and constraints. Workflow designs for crowdsourcing refers to the process of planning and executing the complex set of tasks that can be accurately solved by a pool of crowd workers. The workflow can be decomposing larger tasks into smaller subtasks, and composing subtask solutions into the best overall solution. To gain optimal results, a workflow coordinates among the inputs and the outputs of independent human or machine functions [68].

  Many sophisticated workflow algorithms such as iterations for running recursive tasks are required to improve the quality of results. Several research projects explore crowdsourcing workflow designs. Negri *et al.* [108] and Aoki and Morishima [109], for example, applied the divide-and-conquer approach to various crowdsourcing applications. Little *et al.* [52], [110] introduced TurKit as a toolkit for deploying iterative tasks to Mechanical Turk. Initial findings state that iterative workflows improve the quality of results for refining tasks, such as writing or collective brainstorming using multiple workers to build on and improve upon an existing task.

- **Privacy and Security Manager**: This component is concerned with participant privacy and rights, data security, as well as access control and authentication. Geiger *et al.* [111] proposed multiple levels of accessibility of peer contributions: none, view, assess, and modify. Each level reflects the degree of privacy that a crowdsourcing application allows.

  This component aims to provide some degree of protection for the participants' rights when a crowdsourcing platform makes use of participants' data [112]. The participants should be able to use the privacy controls provided by the crowdsourcing system to either remove data or manage how their data is used. However, mobile crowdsourcing systems still face many challenges with regards to security, privacy and trust [23], [38]. The common privacy and security threats include: disclosing user identity, location and activity, combining crowd-sourced data with other user data, lack of user privacy awareness, vulnerability of mobile devices, relying on information that may be inaccurate, and retaliation for reporting sensitive information [26], [113], [114].

- **Crowd Context Storage and Database**: Data repositories such as crowd results, end-user/participant profile and generic/specific knowledge base are kept in the crowdsourcing system's database. The crowd results repository is a temporary data recording the results of relevant crowd tasks. The knowledge base repository stores long-term data which integrates either the conventional data relevant to the tasks or inferred data which is generated based on crowd input. The knowledge base enables the inference process which is useful for inference from past tasks or even learning about workers [115]. Last, user/worker profile repository contains details about the requests and performance of each of the crowd workers. It is useful for the management of workers, routing suitable tasks, rewarding workers and task assignment.

4) END-USER LAYER

End users are requesters who purchase or rent crowdsourcing services with a certain cost. An end user could be an individual or organization or even car users/smart cars who sends service requests to the crowdsourcing back-end platform/server and receives final results from it. The service providers allow requesters to create crowdsourcing tasks and access their results through a User Interface (UI) on web-based or mobile technologies. There are various tasks in crowdsourcing tasks generated by requesters. They can range from recording, acquiring and reporting real-time data to giving feedback to products or services using a mobile phone which is useful for companies in marketing research, product development, promotion and advertising [116]. The specific UI design is required for these kinds of tasks. According to [117], the study reports that UI design acquires even greater significance for crowdsourcing tasks because those tasks are potentially performed by a large number of globally dispersed people. The authors indicate that UI design choices have a significant effect on crowdsourced worker performance and the quality of results. Thies *et al.* [118] suggest that the user interface and task instructions should be simplified and all content contextualised (e.g., translated into local language) in order to achieve a much higher rate of task completion by workers.

B. A GENERALISED DECENTRALIZED MOBILE CROWDSOURCING ARCHITECTURE

In contrast, in decentralized platforms, all computation and communication is performed locally in each peer in an appropriate manner. Each node/peer of the system is equally responsible for contributing to the global result and could be located at different places with the geographic location being relevant to the computational process itself [119]. Thus, each node is able to process and distribute its information without relying on any centralized authority through mechanisms based on its interactions with the environment. In mobile crowdsourcing systems, they generally can be considered as a distributed process of problem solving through a flexible group of human contributors and mobile devices. In decentralized methods, the systems propagate the request/task among many contributors especially on mobile devices, where all computing and communication is operated on locals. Then, these devices are permitted to fully manipulate and distribute the request to others via communication channels [120].

Today, mobile devices such as smartphones and tablets have been extended to incorporate multiple networking interfaces beyond traditional cellular and WLAN capabilities. Such communication interfaces including Wi-Fi direct/Wi-Fi peer-to-peer and Bluetooth enable the devices to discover and connect with each other without relying on cellular carrier networks, wireless access points, or traditional network infrastructure. Moreover, with powerful multi-core processors and several gigabytes of storage space, mobile devices can bring considerable computational power and communication between device-to-device mode with low latency and high bandwidth. In recent years, several crowdsourcing applications based on decentralized approaches emerge to deal with emergency and disaster scenarios such as earthquake and missing people, and crowded scenarios such as stadiums or shopping malls [85].

For example, the application of user-generated replays [121] leverages mobile crowd networks formed by nearby devices that it allows users to capture and share videos in a crowded event e.g. during a sport stadium. In [19] and [20], they propose the mobile crowdsourcing methods that allow mobile users disseminating information about missing people/items and then send notifications to others who are close to where the people/items lost and immediately after they are discovered, the locations will be determined.

Phuttharak and Loke [36] investigated task propagation models devised to support mobile crowdsourcing in intermittently connected opportunistic networks. The study simulates the distribution of crowd tasks in mobile crowdsourcing networks with limited communication ranges and explores the factors that impact on crowd task propagation and the energy usage for each node.

Another example is the work by Konstantinidis *et al.* [122] who proposed a framework called SmartOpt for searching objects (e.g., image, video, etc.) which are captured by the user in a mobile social community. The main contribution of SmartOpt is to use location data made available by the crowd to optimize the search process with peer-to-peer systems. This approach is able to minimize energy consumption during searching, reduce the query response time when conducting the search and also maximize the recall rate of the user query.

Constantinides *et al.* [123] extended the sensing capability of smartphones by allowing them to identify their

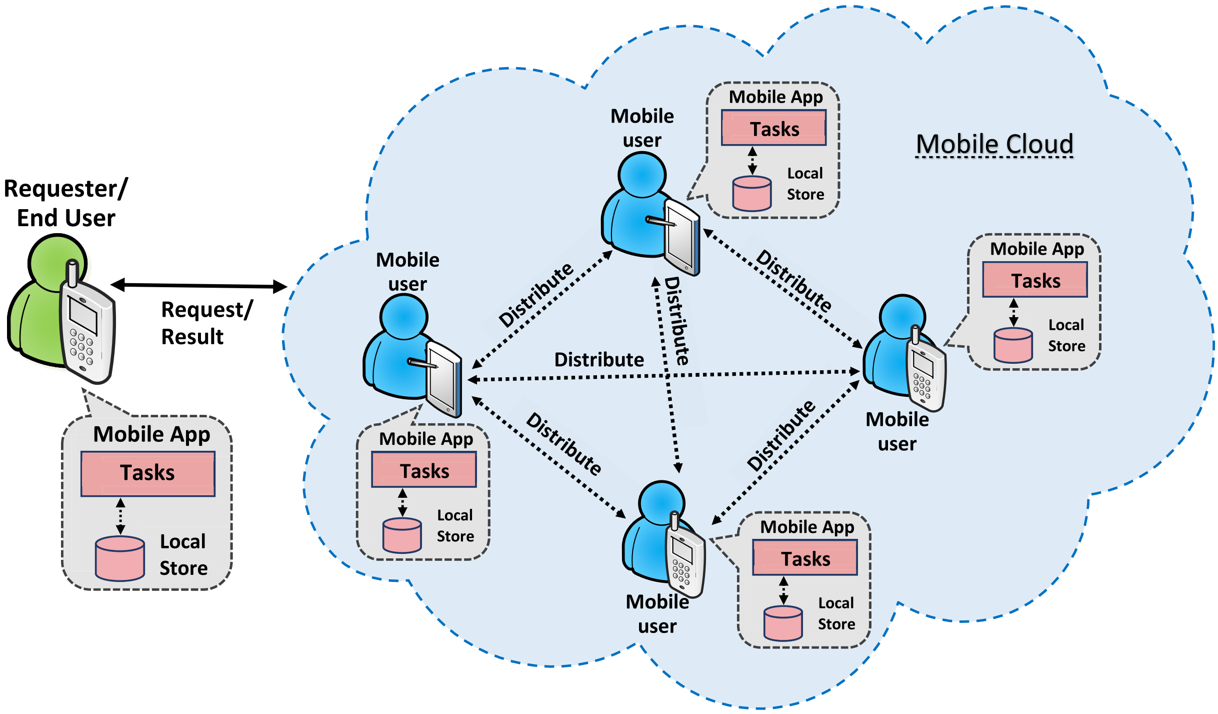

FIGURE 4. Architecture of decentralized crowdsourcing applications.

geographically nearest neighboring nodes in real-time called CrowdCast. This framework is beneficial to the crowdsourcing paradigm since it provides full access to mobile workforces and adds the temporal dimension to location data in order to exploit trajectory-related information.

After reviewing the decentralized approaches in crowdsourcing systems, our proposed generic architecture of decentralized mobile crowdsourcing applications is shown in Fig. 4. The mobile or other stationary devices are the resource providers/workers, and performs, similarly to a mobile peer-to-peer network. Each peer is able to communicate and exchange data with each other in the local vicinity and also can be asked to contribute to identifying mobility patterns or the popularity of a given trajectory. Moreover, they are involved explicitly or implicitly (e.g., by allowing the capturing of sensor data by their mobile devices in the background) in the crowdsourcing process. The captured data is stored and processed in the local database on the mobile device.

C. CENTRALIZED VERSUS DECENTRALIZED MOBILE CROWDSOURCING ARCHITECTURES

We have discussed both types of architectures, detailing their primary components. The decentralized architecture is essentially a distributed version of the centralized architecture but include numerous elements for coordinating the peer-to-peer worker selection, task selection, task propagation, and task (and results) processing. Decentralized approaches move functionality of the different layers into the network of devices allowing peer-to-peer processing without all devices connecting to a central controller reducing a bottleneck and allowing in-situ processing, ad hoc organization and horizontal scalability, but at the cost of more complex coordination, no one party having total control over the whole process, and requiring peers to cooperate in relaying tasks and results. Hence, a hybrid approach that has the advantages of ad hoc and distributed processing and the benefits of central coordination and control for certain layers of functions could be explored.

IV. KEY CONSIDERATIONS AND DIRECTIONS IN MOBILE CROWDSOURCING

There are some key challenges and directions of work in the context of mobile crowdsourcing systems - we discuss the following.

A. INFERRING MOBILE CONTEXT AND SPATIAL CROWDSOURCING

In fact, as mobile devices become very common in our daily life style, these devices might carry important user context data, enabling mobile applications to be user centric and adaptive to user requirements. Mobile context-aware computing involves awareness of the device and its environment [3], [38], [89], [124]. Examples of context include geographical mode (e.g. whether the user is on a car bus train or on foot within a circular area), temporal mode (e.g. in given dates, during given hours), the kinetic mode of humans (e.g. walking, standing, jogging, running), user profile (e.g. age, gender), social mode (e.g. in a meeting, on a phone call, watching movie), or occurrence of certain situations (e.g. crowded in the protest, potholes on the road) [3], [85], [125]. As noted in [126]–[128], context is an important issue and needs to be addressed in mobile crowdsourcing systems and its applications. Afridi [129] states that context must precisely be specified on the task in order to deliver and execute the right tasks to the right people in the right circumstances.

Several mobile crowdsourcing applications are location-aware crowdsourcing platforms that share and solve tasks based on either the requester's or the worker's location. It is context dependent and dynamic (time and location) and may have a number of relevant conditions. For example, Tamilin *et al.* [130] discussed context-aware mobile crowdsourcing where the context should maximize conditions for user participation by presenting only tasks relevant to the user, with minimal user intervention and minimizing the consumption of resources of mobile devices, especially the battery. According to [131]–[134], context-aware applications are not used by individual users, but a group of users. The authors propose a context-aware organization model for mobile collaboration which manages groups in mobile environments with solutions including a special weighted majority voting algorithm. And based on their approximate strategy, they are able to represent a way to make decisions and recommendations in collaborative mobile environments.

In the past few years, a new paradigm of data collection called *spatial crowdsourcing* (SC) has emerged. SC requires workers to physically be at specific locations to complete the tasks i.e., taking pictures or collecting air quality information at specified locations of interest. Sometimes it is referred to as location-aware or geo-crowdsourcing that enables people to gather, analyze, and disseminate geographical and/or social information in the physical world. For example, Microsoft research [135] has a project exploring the use of spatial context in crowdsourcing. They studies how to get people to do simple tasks at specific locations. gMission [136] is also another such platform which features a collection of techniques including geographic sensing, worker detection, and task recommendation to address the needs of getting information related to geographic location. A recent survey [23], [137], [138] thoroughly discussed the core issues of SC, including task assignment, incentive mechanism, privacy protection, the absence of real-world datasets, scalability and quality of reported data. One of the major challenges with SC is the task assignment. Tong *et al.* [138] categorized task assignment in spatial crowdsourcing into static (offline) and dynamic (online) scenarios. In static scenarios, most efforts maximize the total number of valid assigned pairs (tasks and workers) [139]–[144]. Meanwhile, online scenarios aim to maximize the number of assigned worker-task pairs under a budget constraint where workers appear dynamically on platforms. Existing solutions often develop two-sided online matching algorithms to adapt the subsequent unknown arrival objects [145]–[148]. Privacy and trust issues in SC are important to protect workers' privacy and verify the validation of the results provided by workers. Recently, many related approaches have been proposed to cope with the location privacy issue for this type of crowd wisdom [149]–[152]. These methods address privacy by masking the location information based on a differential privacy approach [149], [153].

A key point to note here is that mobile context is crucial in many mobile crowdsourcing applications, but comes often with trading-off privacy, especially in centralized crowdsourcing approaches - e.g., in many applications assigning of tasks to users require the central assigner knowing the context of users/devices. Decentralized approaches where context is used to perform tasks locally and not shared out has an advantage - e.g., a task requirement can be forwarded among peers for local evaluation of suitability to perform the task till it reaches a peer with the right context for it, though a less efficient approach compared to centralised task allocation. Challenges include defining the right context information at the right level of detail for a given crowdsourcing application and obtaining such context information accurately.

B. ENERGY CONSIDERATIONS

Energy consumption of mobile devices, such as smartphones, has increasingly become a concern from various sectors, ranging from smartphone manufacturers, mobile developers, to end users. The embedded sensors in the mobile devices are major sources of power consumption. Even though battery capacity has been increasing in the past few years, the battery life of mobile devices is not catching up proportionally for a large spectrum of current applications [154].

Work in [155]–[157] have studied the energy consumption characteristics of mobile network technologies that are under widespread use today. According to [155], they conducted a measurement study to quantify the energy consumed by data transfer across 3G, GSM, and WiFi. They found that the transmission energy consumed by Wi-Fi is significantly smaller than both 3G and GSM, especially for large transfer sizes. Xiao *et al.* [157] measured the energy consumption for Youtube video streaming applications in mobile phones based on network access technology (WCDMA and WLAN). The results show that network transmission using WCDMA consumes more energy than when using WLAN. These mean that there are additional energy costs for mobile users which can affect the adoption of mobile crowdsourcing.

In mobile crowdsourcing, its applications have deployed mobile sensors to form interactive and participatory sensors networks in order to enable public and professional users to gather, analyze, or even share local knowledge. However, participation in these systems can easily expose mobile users to a significant drain on already limited mobile battery resources. Energy is consumed in all aspects of applications ranging from sensing, processing and data transmission in mobile crowdsourcing. Energy consumption is one of key factors affecting users' willingness to participate in crowdsensing tasks [22], [158]. Thus, there is a strong need for efficient techniques to enhance energy optimization, which will help mobile users retain the benefits of mobile crowdsourcing.

There has been progress in energy optimization on mobile sensing applications in recent years. Several studies try to reduce overall energy consumption in mobile crowdsourcing systems with less collected and uploaded data (i.e., reducing total sensing data collection consumption, total local analytics consumption, and total sensing data report consumption) [36], [128], [158]–[161]. For example, Zhuang *et al.* [162] present an adaptive scheme for obtaining phone location by switching between the accurate but energy-expensive GPS probing to energy-efficient but less accurate WiFi/cellular localization. Lane *et al.* [18] proposed a system for collecting mobile sensor data from smartphones called Piggyback Crowdsensing. They found that collecting mobile sensor data from the smartphone can be performed properly in a background process while a user is operating regular activities such as placing phone calls or using applications. So, the energy overhead of user participation is lowered and the phone need no longer be woken from an idle sleep state.

Recently, Montori *et al.* [163] proposed a probabilistic distributed algorithm (PDA) to save energy limiting overhead and data redundancy. The algorithm exploits feedback from the central authority to set probabilistic thresholds for sensing decisions in each region of interest. Moreover, there are many frameworks proposed in the task assignment phase to keep the energy consumption of each mobile device low [164], [165]. For instance, [164] and [165] proposed approaches to select a minimum number of workers while ensuring a predefined sensing quality. However, the diversity of quality and energy consumption of the sensed data poses an obstacle for improving the quality of data with low energy consumption. Therefore, it is still a challenge to improve the quality of data and minimize energy consumption.

A key point to note is that the use of GPS, data transfer (whether relaying data in peer-to-peer decentralized crowdsourcing networks or sending to central controllers), screen utilization when users perform tasks and even phone calls (if an application requires it), are key energy-consuming functions typically required in mobile crowdsourcing. Also, battery life improvements on mobile devices have been substantial but certainly not at a rate where energy consumption of applications can be ignored - hence, mobile crowdsourcing applications will need to take into account energy considerations, and the quality of crowdsourcing results and willingness to participate can be impacted by energy limitations, as noted above.

C. TASK ALLOCATION AND COMPUTATION

In mobile crowdsourcing, task allocation aims to allocate a specific set of outsourced tasks to a set of mobile users who can potentially finish these tasks more accurately and efficiently. For example, if the task is to translate Japanese language to English, the mobile users who know in Japanese language or live in Japan might be preferred to be recruited in the task.

There are many studies investigating task allocation [39], [166]–[168]. An *et al.* [39] proposed a crowdsourcing assignment model based on social relationships and community detection. The simulation results show that their crowdsourcing assignment approach has better performance in terms of correctness, effectiveness, and robustness in a mobile-aware scenario. According to [166], they proposed a budget-optimal task allocation algorithm for effectively assigning the task for appropriate workers. The study provides a non-adaptive task allocation scheme and an inference algorithm based on low-rank matrix approximations and belief propagation. Later, Ho *et al.* [167] explored the task assignment problem by applying online primal-dual techniques. They also proposed a near-optimal adaptive assignment algorithm. The result shows that adaptively assigning workers to tasks can lead to more accurate prediction and lower cost when the available workers are diverse. Moreover, Reddy *et al.* [168] claim geographic and temporal availabilities of mobile users would highly impact the task delay, which should be considered in participant selection.

With the dynamic conditions of the set of mobile devices, local analytics performing certain primitive processing of the raw data on the device are needed. The results are initially computed before shipping the processed data back to the server for further processing and consumption. For instance, in inferring human activity applications [169], [170], local analytics is done using phone classifiers that perform complex data analysis such as feature extraction, decision tree classifications and data stream mining before transmitting it to the server. Ganti *et al.* [22] noted two benefits for motivating localized computation. First, the overall processing performed consumes less energy and bandwidth than transmitting the raw data. Second, it is able to minimize the amount of processing in the server.

Mobile devices are connected only intermittently when they opportunistically contact each other, known as Delay Tolerant Networks (DTNs). DTNs use a store-carry-forward paradigm to allow communication when a path through the network is not reliable due to frequent disconnections. With the unreliability and dynamism of mobile networks, there are several key issues for the development of crowdsourcing-related mobile applications that need to be considered. Due to the dynamic nature of moving hosts with may join and leave from the platform at any time, a mobile network topology is likely to change often. Also, communication range might be limited when a mobile user goes outside of a given location, causing unavailability of data (tasks or feedbacks from crowd) in his mobile device at that location. A robust routing protocol is needed when the data needs to be transmitted between the two nodes. In [171] is a survey on opportunistic routing for delay tolerant networks. They classified the routing techniques of opportunistic network and also evaluated the performance of each method.

Recently, Socievole *et al.* [172] used social information extracted from multiple social networks to improve message delivery in opportunistic networks. The multiple social networks are based on a social metric which exploits social information extracted from different network layers, in which a node forwards packets using a routing metric that combines three measures: node centrality, tie strength and a tie predictor. Meanwhile, Chaintreau *et al.* [173] used Online Social Networks (OSN) to take advantage of node mobility in an opportunistic manner. The models show that the induced topology supports well a decentralized routing scheme (i.e. greedy routing) and a spatial gossip mechanism when nodes maintain connections with other nodes that they have met in the past.

The issues of task allocation, worker selection, and worker discovery in mobile crowdsourcing are complex, ranging from centralised task allocation approaches to more ad hoc decentralised approaches. Depending on the task, whether requiring results in real-time or over longer periods, the appropriate task allocation and worker selection algorithm is required. Delay Tolerant and opportunistic types of task dissemination and worker discovery may be appropriate in situations of poor or intermittent connectivity, or where the pool of potential workers in the vicinity might be varying for a given task, but applicable only when results are not required in a short time or in real time.

Also, task self-selection by workers versus task allocation (and worker selection) by a central controller are two strategies, each with its own advantages. In open environments, there may be little prior knowledge of workers and difficulties in tracking the behaviour and performance of workers (and workers may have no prior reputation information).

In a given mobile crowdsourcing application, for tasks to be matched with workers appropriately, how tasks need to be described and workers need to be profiled are considerations.

D. PRESERVING USER PRIVACY

For widespread deployment and acceptance of mobile crowdsourcing, privacy considerations must involve both service providers and mobile users/workers. For example, the research reported in [174] found that 82% of active Facebook users disclosed personal information such as their birth date, cell phone number, personal address, political and sexual orientation, and partner's name. This vulnerability permits legitimate applications to gather sensitive personal information without the users' full awareness. Moreover, the recording of intimate discussions, taking photographs of private scenes, or tracing users' paths and monitoring the locations they visited are possible. In mobile crowdsourcing, the crowd tasks could expose the personal interests and aims of service consumers. Likewise, the feedback from workers generally tagged with spatio-temporal information discloses abundant personal information on mobile users, such as location, personal activities, and social relationships. As a result, privacy preservation is of paramount importance in mobile crowdsourcing.

In general, user information can be protected from the intruder by using cryptography when transmitting and processing data. Liu *et al.* [175] proposed a collaborative learning scheme for classification tasks, e.g., activity or context recognition, in mobile sensing, which can ensure the classification accuracy without compromising mobile users' privacy, by utilizing feature perturbations and regression techniques. Chon *et al.* [176] proposed a 24 hour time lapse during which users can manually review and delete any data which they deem too sensitive to share. Users also have the ability to block the transmission of data in advance when anticipating activities of a sensitive nature. Anonymity, as an effective solution for privacy preservation, has also been adopted to preserve mobile users' privacy in mobile crowdsensing [2]. Cornelius *et al.* [64] proposed the AnonySense architecture as a means of protecting user privacy when reporting context sensitive information, as it offers protection across multiple layers without manual intervention from the user. It allows using anonymous nodes for delivery of tasks and submission of reports. Ren *et al.* [2] suggested that anonymous techniques should be carefully developed for information transfer in local-based mobile crowdsourcing since local servers are generally deployed for commercial purposes and not trusted by mobile users.

We have noted earlier that the context privacy and utility trade-off is a consideration when developing a mobile crowdsourcing application requiring user contexts. However, it is not only the privacy of contexts used in determining who to assign a task to, but the the privacy of data supplied when users perform tasks, which depends on the task requirements - e.g., if the task is to crowdsource what people eat in a large shopping mall, requiring crowdsourcing pictures of what is being eaten at a particular time and location, this may not be comfortable with everyone.

E. HETEROGENEOUS DATA FORMATS AND MODALITIES

The range of mobile, wearable, and vehicle (e.g., bicycles, cars and drones) sensors and devices continues to grow, so that there is an increasing range of types and formats of data that can be collected via such devices. The data could be in different formats and collected via different user-device interaction modalities. For example, suppose one is crowdsourcing video feeds of a large tourist park area - the video can be captured via smartphones, smartwatches (with embedded cameras), on-car cameras, as well as portable GoPro devices, with a need to meaningfully integrate such a diverse range of video formats, resolution, time-frames, and points-of-view.

Also, some of the data crowdsourced might be done through different types of networks. For example, some data might be collected via linkages in different types of social networks (via 4G/5G Internet) and some collected via direct peer-to-peer localised networks using Bluetooth or WiFi-Direct based connectivity. While such a diversity of networking capabilities exists, with a wider range of channels by which workers can be reached, there is a need to ensure that data collected can be collected and aggregated appropriately. This also implies a design consideration of what types of data formats, modalities and networks be best employed for a given mobile crowdsourcing application.

F. FROM MOBILE CROWDSOURCING TO THING CROWDSOURCING

From an era of mobile computing, we are now well into the era of the Internet-of-Things (IoT) [177]. Mobile crowdsourcing ideas can serve as a critical building block for the emerging IoT, leading to a notion of *thing crowdsouring*, generalising from mobile crowdsourcing so that not just smartphones, but smart things (from phones, cameras, vehicles, drones, to everyday objects with embedded computational ability) can enlist workers to solve problems - e.g., a device is not able to process a particular image and enlists human workers to solve this problem, or it could enlist other things with the resources to address the problem. Potentially, thing crowdsourcing enables a new way for things to perceive the world extending the services the IoT can offer. While things can connect to Amazon's Mechanical Turk or other microtasking platforms via the Internet, things could utilise other nearby edge devices, using direct interconnections among things to things, and things to people, and perform computations locally [178].

In this regard, the potential of IoT can be enlarged through this method of crowd-empowering things. Things can crowdsource task to other things and people, but also be providers of resources, or act as the means through which people can perform micro-tasks. This is made more feasible today and increasingly so in the future due to the rising Internet-of-Things where things are increasingly connected to other things via short-range networking technology or the emerging wider-range 5G networks, and by AI embedded in things, i.e. things are programmed with an intelligent problem-solving strategy, e.g., to first attempt to solve problems initially by themselves, but then will crowdsource tasks to other things or even via a thing social network[15] to get help in solving problems, with the ability to combine crowdsourced results (e.g., in a human-AI synergy mediated by things).

Considerations with machines crowdsourcing tasks to other machines (or humans) are similar to that in humans crowdsourcing tasks to others. Thing crowdsourcing will also face technical challenges, such as data redundancy and quality of service, integration methodology, robustness of connections, scalability and flexibility, power and energy efficiency, and security and privacy protection.

V. CONCLUSION

The emergence of the mobile crowdsourcing paradigm has brought a dramatic change in the landscape for solving complex problems. Mobile crowdsourcing refers to a powerful approach utilizing mobile sensing and human intelligence to address problems and finding relevant solutions. Recently, crowdsourcing has steadily moved across many disciplines in both scientific and industrial sectors. It has developed in new contexts such as new business ideas and solutions to social problems and consequently, there are new products and services being launched that are leveraging the power of the crowd to find solutions to problems. The mobile crowdsourcing paradigm provides a new method for perceiving the world, by involving anyone in the process of sensing, for greatly extending the services of IoT and building a new generation of intelligent networks that interconnect things-to-things, things-to-people, and people-to-people.

We have given an extensive survey of current mobile crowdsourcing research that is able to serve as a useful reference for future research in the area. We reviewed background knowledge on mobile crowdsourcing and discussed a range of frameworks, architectures, techniques, and directions for developing mobile crowdsourcing applications. We also presented a taxonomy of the issues found in this area and four aspects along which these issues have been tackled, focusing on applicability, generalised architectures and the support for mobility. Finally, we proposed a generalisation from mobile crowdsourcing to thing crowdsourcing.

[15] For example, see http://www.social-iot.org/

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