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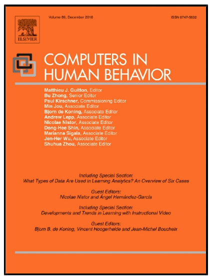

Mobile Crowd Sensing – Taxonomy, Applications, Challenges, and Solutions

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Mobile Crowd Sensing – Taxonomy, Applications, Challenges, and Solutions

Abstract:

Recently, mobile crowd sensing (MCS) is captivating growing attention because of their suitability for enormous range of new types of context-aware applications and services. This is attributed to the fact that modern smartphones are equipped with unprecedented sensing, computing, and communication capabilities that allow them to perform more complex tasks besides their inherent calling features. Despite a number of merits, MCS confronts new challenges due to network dynamics, the huge volume of data, sensing task coordination, and the user privacy problems. In this paper, a comprehensive review of MCS is presented. First, we highlight the distinguishing features and potential advantages of MCS compared to conventional sensor networks. Then, a taxonomy of MCS is devised based on sensing scale, level of user involvement and responsiveness, sampling rate, and underlying network infrastructure. Afterward, we categorize and classify prominent applications of MCS in environmental, infrastructure, social, and behavioral domains. The core architecture of MCS is also described. Finally, we describe the potential advantages, determine and reiterate the open research challenges of MCS and illustrate possible solutions.

Keywords: Mobile Crowd Sensing, Multifacted Infrastructural and Human-Powered Applications, Social and Behavioral applications, Large-scale Sensing, Communication, Computing.

1. Introduction

In recent years, with the advancements in mobile and wireless communication technologies (e.g., 4G/5G), efficient and high capability networks have emerged allowing better connectivity to billions of ubiquitous smartphones and vehicular systems. Alongside the growth of mobile networks, plethora of sensing devices have been integrated into smartphones and vehicular systems enhancing thus their sensing capability. Moreover, they are fitted out with more processing power and storage capacities. This joint evolution led to an emergent paradigm named Mobile Crowd Sensing (MCS).

MCS is an emerging sensing and geo-crowd sourcing paradigm, based on the mobile device's sensor, that enables acquiring local geospatial information and knowledge and giving the possibility to share this information/knowledge with other users and wider community [1, 2]. MCS has been also defined by

Raghu Ganti as the data sharing and information extraction process, based on the collaboration of individuals with sensing and computing devices, to measure and enumerate mutual interest phenomena [3]. Other researchers also formally define MCS as a large-scale sensing paradigm based on the power of user-companioned devices (including mobile phones, smart vehicles, wearable devices, and so on) to contribute sensed or generated data from their mobile devices and aggregate and fuse the data in the cloud for crowd intelligence extraction and human centric service delivery [4].

Indeed, the urbanization of the world population and the fast growth of smart cities [5] make MCS a promising research area that enables innovative techniques and systems which exploit data and communications technologies in order to enhance their functions, improve efficiency, and the economy and offer the best environment for their citizens. MCS enables a plentiful number of individual mobile phones and vehicular devices to share local knowledge (e.g., local information, ambient context, noise level, and traffic conditions) collected by a myriad of embedded sensors (e.g., GPS, digital compass, microphone, light sensor, and accelerometer). The application of analysis, reasoning and data mining techniques on the shared sensed data provides useful insights for smart urban space monitoring and might have an enormous societal impact.

Despite the recent emergence of the MCS concept, there are some fruitful research works in the literature that addressed the crowd sensing before. In [6], the authors introduced the crowd wisdom concept which demonstrates that decisions made by a group of people have better results than those made by a single person. Four quality metrics have been proposed to define the efficiency of the crowd: diversity in opinion, independence of thinking, decentralization, and opinion aggregation [7]. Another notion close to the crowd sensing concept, named participatory sensing, was proposed in [8]. The main idea is to charge individual mobile devices to build participatory sensor networks that enable collecting, evaluating, and sharing local knowledge. Compared to the participatory sensing which is only devoted to public sensing, MCS involves both personal and public sensing. Moreover, explicit and implicit user participation is considered in MCS while participatory sensing involves only explicit user participation.

Mobile crowd sensing have been the subject of several review papers in recent years. Nicholas D. Lane et al. presented one of the first survey papers on MCS, describing the existing mobile phone sensing algorithms, applications, and systems [9]. Furthermore, the authors discussed the emerging sensing paradigms, and formulated an architectural framework. Similarly, Khan, Wazir Zada et al. presented a comprehensive study on all the MCS systems which use smart phones and mobile phone sensors for humans good and for better human-phone interaction [10]. Bin Guo et al. presented a review study which characterizes the unique features and novel application areas of MCS, and proposed a reference framework for building human-in-the-loop MCS systems. Also, further clarification about the complementary nature of human and machine intelligence have been presented in [8]. Another paper that serves the MCS was presented by Huadong Ma et al., where opportunistic characteristics of human mobility were investigated from the perspectives of both sensing and transmission [1]. Also, the authors have discussed how to exploit these opportunities to collect data efficiently and effectively

The mobile crowd sensing remains an attractive research area and numerous research works have been proposed recently. Indeed, the application field continues to grow and several challenges and solutions have emerged. To the best of our knowledge, none of the existing studies investigated various aspects of MCS which are explored and presented plored in this article. Therefore, it is very interesting to investigate the last emerging challenges and solutions for MCS and highlight the introduced advantages and opportunities. The contributions of this study are summarized as follows:

- We highlight the distinguishing features of MCS compared to WSN and describe its potential advantages.
- We present a taxonomy of MCS based on sensing scale, level of user involvement and responsiveness, sampling rate, and network infrastructure.
- We also categorize, classify, and briefly describe MCS emerging applications into environmental, infrastructure, social, and behavior.
- We describe the architecture of MCS based on the provided services and the interacting entities.
- We present the main features and advantages of MCS and expose the key architectures and the application domains.
- We identify, and reiterate the main challenges of MCS and outline the current MCS strategies and solutions.

The paper is organized as follows: Section 2 highlights the distinguishing features and advantages of MCS compared to it's predecessor i.e., wireless sensor network (WSN). Section 3 inroduces a taxonomy of the MCS. Section 4 presents an overview of the main MCS applications. In section 5, we present a typical MCS architecture based on the provided services and the interacting entities. Section 6 points out the current MCS strategies and solutions. Finaly, we conclude the paper in section 7.

2. MCS vs. WSN: Unique features and benefits

Although MCS can be considered as an evolution of sensor network, however, it has several unique characteristics and advantages compared to traditional WSN.

2.1 Resource capacity

Unlike resource-constrained WSN, MCS is based mainly on mobile phones, which are equipped with much more resources in terms of computing power, memory storage, communication range, and energy supply. Moreover, a rich set of sensors is integrated in mobile phones, such as camera, GPS, accelerometer, microphone, gyroscope, while traditional sensor devices are dedicated to sense limited sensing values. Following the fast advances in smartphone technologies, innovative smart devices, such as smart watch, smart glass, and smart clothes are expected to be a part of MCS network enabling thus more insightful applications and services.

2.2 Network deployment and coverage

The deployment of traditional WSN is often difficult and might be expensive. On the other hand, MCS platforms are quite low cost and there is no need to network deployment as billions of mobile phones are already deployed in the field. Therefore, large-scale sensing networks can be built with low cost in less time compared to WSN. The network coverage represents another important MCS characteristic over WSN. Indeed, the smart device users are often mobile which provides an outstanding spatiotemporal coverage compared to traditional static WSN deployments.

2.3 Hybrid sensing approach

MCS is mainly based on a hybrid sensing system where humans and machines are both involved in the sensing task. Compared to WSN, MCS offers a smart sensing process as it takes benefit of the human intelligence. Indeed, contributors can control the sensing process by deciding what to be captured. Also, smart phones can capture contributors' feelings or remarks regarding the readings, which optimizes the sensing efficiency. Thus, without requiring sophisticated hardware and software, higher quality or semantically complex data can be collected by exploiting the intelligence and mobility of humans.

2.4 Heterogeneous network connectivity

Based on the MCS requirements and available network infrastructures, mobile phones and devices are interconnected through different networking technologies. For example, GSM can be used for large scale connectivity while Wi-Fi and Bluetooth can used for short-range communications. Indeed, MCS enables an interconnection medium which supports transient networking services, such as connectivity, collaborative sensing, and data routing/transmission, for the participants crossing these multiple wireless networks [7].

2.5 Network disruption tolerance

Due to the irregular network connectivity in some cases (e.g., low signal strength due to interference or no signal in a rural area), efficient links between mobile phones could not be guaranteed. This disrupted network nature can be tolerated by most of MCS applications. Indeed, real time transmission of individual sensed data is not always imposed and MCS applications can tolerate also, in some cases, a low degree of data accuracy. Mobile crowd applications enable disruption tolerance services based on data storage strategies where captured data are stored locally before their deliverance when the network connection is available.

2.6 Wireless networking technologies

Several wireless networking technologies can be involved in the mobile crowd sensing process. Indeed, the mobile crowd sensing participants can communicate in short distances using short rang wireless network technologies (e.g., Bluetooth, and Wifi). On the other hand, 5G networks can be employed for long range communication of sensed data from all kinds of mobile devices with various wireless interfaces.

2.7 Sensing platforms

MCS is made around several hybrid sensing platforms from classical WSNs to newly widely held mobile devices such as: smartphones, tablets, smart watches, smart glasses and smart bracelets. The fast growth in internet of things and sensors technologies will lead probably to the emergence of more mobile sensing platforms.

Indeed, the unique features of MCS enables plethora of novel applications compared to the classical WSN. The resource capacity of the crowd sensing devices (GPS, accelerometer, microphone, gyroscope etc.) can be exploited in variety of sensing applications. Moreover, the networking connectivity, allows large scale deployment of MCS applications.

3. MCS taxonomy

Before surverying the main applications, challenges and solutions, we devise a taxonomy of mobile crowd sensing based on the existing literature. From scalability point of view, mobile sensing can be categorized as follows.

- <u>Separate sensing</u>: there is no collaboration in the sensing process, and the data are gathered individualy for personal use only.
- <u>Cluster sensing</u>: a group of users with common interests collaborate and share the collected data.
- <u>Community sensing</u>: large call sensing based on peoples' communities which collaborate to predict the global trends.

Another taxonomy approach is based on the involvement level of individuals that participate in the sensing process. In this taxonomy, we can categorize the sensing approach as opportunistic, participatory, and hybrid sensing (a mixture of user control and device processing). In the opportunistic sensing, the data is collected in an automatic manner with low user involvement. The participatory sensing operates in a different way and requires the users participation in the data collection activity. Also, the user responsiveness to the sensing process can be considered as implicit or explicit.

From the viewpoint of the sampling rate, the data sensing can be performed continuously or executed depending on a specific context (certain time periods or places). However, the continuous sensing may exhaust the sensing resources while the context aware sensing will be inefficient to monitor dynamic events. Regarding the network infrastructure, the MCS can exploit the existing infrastructures (e.g., access points and GSM). Otherwise, the adhoc infrastructure can be adopted forming thus opportunistic networks. Also, a hybrid infrastructure can be used based on adhoc and existing network infrastructures.

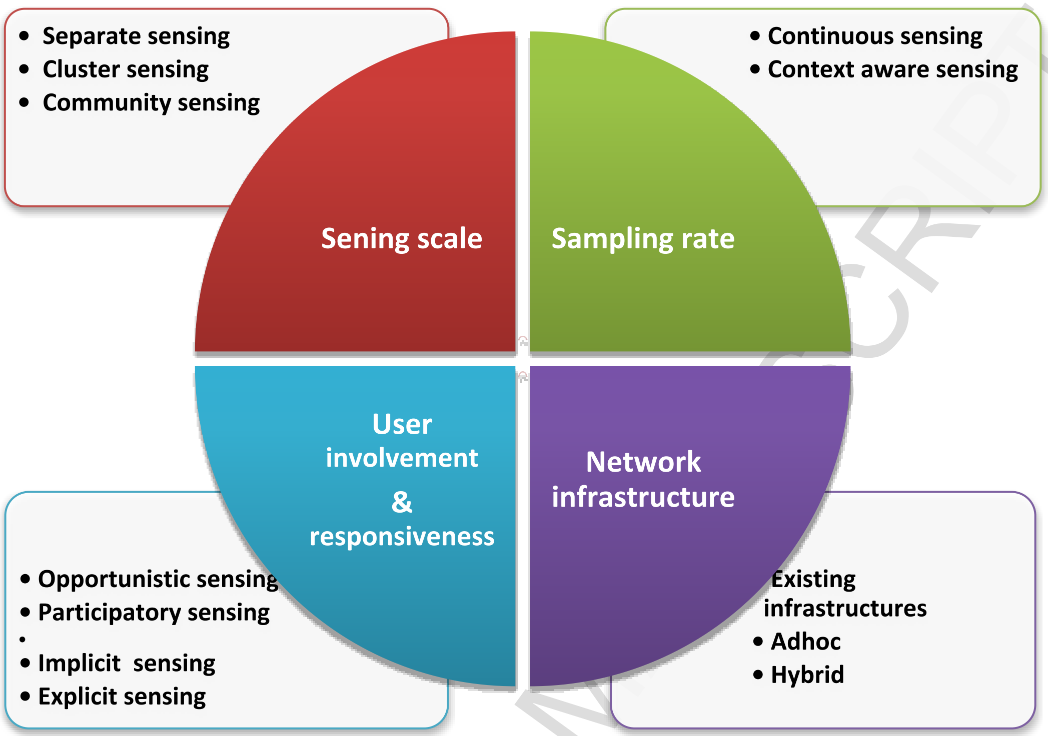

Figure 1. MCS taxonomy.

4. MCS Application domains overview

MCS has opened several application opportunities in various domains. These domains can be classified, as presented in figure 2, in four main categories based on the type of sensed phenomenon: Environmental, Infrastructure, social, and behavior [3]. In this section, we review state-of-the-art MCS applications and projects.

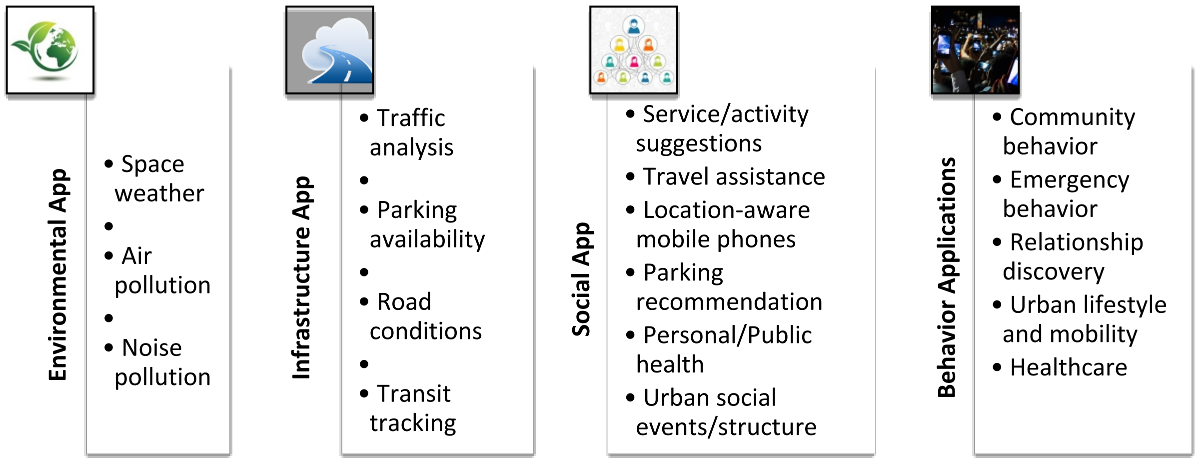

Figure 2. MCS applications' categories.

4.1 Environmental applications

The applications of MCS in the environmental field aims to basically preserve the nature and monitor the space weather and air and noise pollution levels. In the last decade, several scientific studies have been conducted based on mobile devices of volunteer contributors.

- **Space weather**: a recent report by the National Research Council of the National Academies [12] has exposed the benefits of applying crowd sensing for weather monitoring. To optimize the efficiency of air temperature monitoring systems, user's smartphones are exploited to establish a worldwide temperature sensor network at low cost and in an automated fashion. Thus, there is no need for installing the expensive and limited area weather stations which moreover require maintenance. One of the relevant examples of MCS application for temperature measurement is the employing the Android application Open Signal [13] for smartphones. From 25 April 2012 to 22 April 2013 over 530 thousand devices have contributed a total of over 220 million readings of weather temperatures across more than 200 countries/territories [13]. The Table 1 gives an overall picture of the most known proposed research works and projects that exploit the notion of MCS in weather monitoring field.
- **Air pollution**: MCS can be applied to establish a mobile measurement system which enables the generation of accurate ultrafine particle pollution maps with high spatio-temporal resolution. Volunteers carrying smartphones and sensors contribute the sensed data while all citizens using the application can receive the measurements from the data cloud in real-time and only for the areas of their particular interest [19]. We further summarize, in Table 1, the most representative pollution applications based on MCS.

- **Noise pollution**: Noise pollution is as harmful as air and water pollution, impacting the health and well being of citizens. MCS offers new opportunities in the noise monitoring field, where users' feelings or remarks regarding the readings can be collected by smart phones. Citizens' participation represents an efficient approach of sensing noise levels, as they can instantly sense it using their smart phones and send it to the city officers if the noise is intolerable. Several research works have addressed the MCS applications to monitor noise pollution levels. Table 1 summarizes some of the prominent applications of MCS for environmental monitoring.

Table1. A summary of main MCS applications for environmental monitoring.

Ref	Usage	Description	Involvement of the users in the sensing process	Application domain
[13]	Temperature monitoring	A real-time temperature monitoring system to collect air temperatures based on an Android application for smartphones (Open Signal).	Medium	**Space weather monitoring**
[15]	Temperature monitoring	Atmos: A hybrid crowdsourcing approach to weather estimation. The main idea is to leverage a crowd-sourcing network of mobile devices for the collection of in-situ weather related sensory data, provided by available on-board sensors, along with human input, to generate highly localized information about current and future weather conditions.	High	
[16]	Temperature monitoring	An experimental study to examine the suitability of crowd sourced air temperature measurements from citizen weather stations. A large number of measurement readings, from up to 1500 stations with reference air temperature in Berlin and surroundings, have been compared to a period of twelve months (Jan-Dec 2015).	Low	
[17]	Winter precipitation monitoring	mPING: An efficient crowd sensing app for smartphones which allows citizen scientists to provide observations about the winter precipitation type at the surface at least equivalent in quality to human-augmented Automated Surface Observing System (ASOS) observations.	High	

[18]	Pressure monitoring	PressureNet: MCS based application that collects atmospheric pressure measurements from its users, with the aim of using this data to help understand the atmosphere and better predict the weather.	Medium	
Ref	**Usage**	**Description**	**Involvement of the users in the sensing process**	**Application domain**
[20]	Air pollution	N-Smarts: pollution project, which uses sensors attached to GPS enabled smart phones to gather data, in order to help to better understand how urban air pollution impacts both individuals and communities.	Medium	**Air pollution monitoring**
[19]	Air quality monitoring	Energy efficient urban crowd sensing application for air quality monitoring based on the use of wearable sensors and mobile devices. The application also provides a personalized real-time alert mechanism to mobile users.	Low	
[21]	Carbon dioxide monitoring	PEIR: a participatory sensing application that uses location data sampled from everyday mobile phones to calculate personalized estimates of environmental impact and exposure.	Medium	
[22]	Air pollution	A mobile crowd application which uses data gathering software run on residents' mobile phones to gather the information of on-the-road diesel trucks to study community exposure to urban air pollution.	Low	
[23]	Pollution exposure estimation	ExposureSense: a hybrid mobile participatory sensing infrastructure that integrates the WSN and MCS paradigms. ExposureSense is able to monitor people's daily activities as well to compute a reasonable estimation of pollution exposure in their daily life.	Low	
[24]	Air quality monitoring	UAir : inferred fine-grained air quality information of a city based on heterogeneous crowd sourced data, including the air quality, traffic flow, human mobility, structure of road networks and points of interest (POIs).	Low	
[25]	CO_2 pollution monitoring	BikeNet : an extensible mobile sensing system which leverages personal, bicycle, and environmental sensing using dynamic role-assigned bike area networking to measure and	Medium	

		report the CO_2 pollution level.		
[26]	Air pollution monitoring	HazeWatch: A Participatory low-cost participatory system for urban air pollution monitoring in Sydney. Several low-cost mobile sensor units attached to vehicles are used to measure the air pollution concentrations, and the users' mobile phones are leveraged to tag and upload the data in real time.	Medium	
Ref	**Usage**	**Description**	**Involvement of the users in the sensing process**	**Application domain**
[27]	Personal noise monitoring	NoiseTube: enables citizens to measure their personal exposure to noise in their everyday environment by using GPS-equipped mobile phones as noise sensors.	High	**Noise pollution monitoring**
[28]	Noise levels monitoring	NoiseSPY: turns the mobile phone into a low-cost data logger for monitoring environmental noise. It allows users to explore a city area while collaboratively visualizing noise levels in real-time.	High	
[29]	Real-time noise maps	NoiseMap: smart phone application based on participatory sensing leading to accurate, real-time noise maps.	Medium	
[30]	Noise pollution monitoring	NoiseBattle & NoiseQuest: MCS application for gathering noise pollution data. The applications are designed following gamification techniques to encourage users to participate using their personal smartphones.	High	
[31]	Reginal noise levels monitoring	NoizCrowd: allowing to crowd source noise levels in a given region and to generate noise models by using state-of-the-art noise propagation models and array data management techniques.	Low	
[32]	Noise visualization map	SoundOfTheCity: a smart phone application that allows the users to continuously measure the loudness of their environment. The measured data are anonymised and sent to a central server where all the generated information from the voluntary participants on a city scale are aggregated and mapped to a meaningful noise visualization map.	High	
[33]	Noise pollution monitoring	Ear-Phone: a context-aware noise mapping using Smart phones.Ear-Phone investigates the use of different interpolation and regularization methods to address the fundamental problem of recovering the noise map from incomplete and random samples obtained by crowdsourcing data	Low	

		collection.		
[34]	Urban noise monitoring	MCS-based system allowing users to gather noise measurements in order to perform large-scale, low-cost and sufficiently accurate urban noise monitoring campaigns.	High	
[35]	Noise pollution monitoring	MOOL: a platform that adopts the MCS paradigm for involving secondary schools' students in didactic experimentation about acoustics and noise sensing.	High	

4.2 Infrastructure applications

Infrastructure monitoring represents a proliferate application field for MCS, which consists of large scale measurement of phenomena related to public infrastructure involving traffic congestion, parking availability, road conditions, real-time transit tracking [36], power line condition [37] and outages of public works (e.g. Broken traffic lights or malfunctioning fire hydrants).

Traffic analysis and transit tracking represent the most addressed application fields in the infrastructure monitoring. One of the first researches that introduce the use of the crowd sourcing concept in traffic management was proposed by G.L. Graunke. A large amount of traffic information is available from a variety of sources. This information may be used by drivers to attempt to select from among a variety of potential routes to travel to a given destination [38]. Nericell represents another traffic congestion control system based on the use of the accelerometer, microphone, GSM radio, and/or GPS sensors embedded in user's phones to detect potholes, bumps, braking, and honking [39].The traffic congestion problem was also addressed in [40] where a MCS system was proposed based on GPS-equipped taxis to analyze traffic changes around the Olympic games in Beijing. The same idea was also adopted in [41], where floating GPS-equipped car and smart card records from both bus and metro are used for real time data evaluation of urban traffic. The application of MCS in transit tracking was also introduced in [42] where participating users install an application on their smartphones to exploit GPS, WiFi, and accelerometer for transit tracking. CY Lin et al. proposed a novel Comfort Measuring System (CMS) for public transportation systems where GPS and 3-axis accelerometer functions of modern smart phones are used to measure the comfort level of the vehicle rides [43].

To predict a bus arrival time, P. Zhou et al proposed an MCS system based on bus passengers' participatory sensing [44]. SmartRoad is another traffic monitoring application which introduces a road sensing system that generates and collects mobile sensory data from vehicle-resident mobile phones [45].

TrafficInfo represents an MCS application which implements a participatory sensing based live public transport information service [46]. In [47], the authors proposed enviroCar which represents a new platform for collecting traffic and related environmental data from automobile equipped with On-Board Diagnostics (OBDII) and Android smartphone. J. Wan et al proposed a MCS technology to support the creation of dynamic route choices for drivers wishing to avoid congestion [48]. In [49], the authors proposed a cloud-assisted MCS architecture for urban transportation system where traffic congestion is controlled based on sensed data obtained continuously from a large set of smartphones carried by drivers. A. KAUR et al. proposed an efficient and cost-effective method using smartphones to determine the traffic state of the road [50]. RoadCrowd represents a novel traffic estimating methodology, which was proposed in [51], involving crowd sourcing approach as well as utilization of conditional probability distribution of traffic states at adjacent junctions [51].

Several other researches focused on proposing MCS based systems for parking availability management. For example, ParkNet which was proposed in [52] to detect available parking spots in cities using ultrasonic sensing devices installed on cars combined to smart phones. ParkSense represents another smartphone based application that detects the vacated parkingspots based on ubiquitous Wi-Fi beacons [54]. PE. Carnelli et al. introduced a novel vehicle parking activity detection method, called ParkUs to eventually reduce vacant car parking space search times. ParkUs utilizes accelerometer and magnetometer sensors found in all smartphones in order to detect parking activity within a city environment [55]. In [56], a novel automatic parking system was proposed where drivers cooperate to indicate a parking space from the outside of a vehicle and assist the vehicle in recognizing its environment so that the vehicle can park semi-automatically. JG. Krieg et al. proposed SmartPark, a smartphone based system that relies exclusively on the smartphone sensors to automatically point drivers to the nearest parking spot and enables charging them exactly for the amount of time parked [57]. S.Noor el al. introduced ParkBid, a crowd sourcing based parking service for automobiles where the information of free parking is circulated among the interested users following a bidding process [58]. In [59], the authors presented ParkGauge, a crowd sensing-based method to gauge the occupancy of parking garages by leveraging low-power sensors (e.g., accelerometer and barometer) in the driver’s smartphone. F. BOCK et al. presented an evaluation of the suitability of a fleet of taxis as probe vehicles for parking crowd-sensing. The authors exploited a dataset of real-world trajectories collected from about 500 taxis over 3 weeks in San Francisco (USA), to extract their movement patterns [60].

Ground transportation monitoring has also attracted some research works. In [61], Y. Kong et al. proposed a system named CrackDetector to detect cracks and estimate their types and size with smart phone. F. Seraj et al. present a new algorithm for map matching of crowd-sourced measurements for monitoring ground transportation infrastructures using smartphones [62].

Table 2. A summary of main MCS applications for infrastructure monitoring.

Ref	Usage	Description	Involvement of the users in the sensing process	Application domain
[38]	Traffic analysis	Predictive traffic modeling	Medium	Traffic management
[39]	Traffic congestion	Nericell: rich monitoring of road and traffic conditions using mobile smartphones	Medium	
[40]	Traffic congestion	Operational analysis on Beijing road network during the Olympic Games	Medium	
[41]	Traffic analysis	Real time monitoring of urban mobility patterns	Medium	
[42]	Transit tracking	Cooperative transit tracking using smart-phones	High	
[43]	Comfort measuring	A comfort measuring system for public transportation systems using participatory phone sensing	High	
[44]	Traffic predition	Predicting bus arrival time with mobile phone based participatory sensing	High	
[45]	Traffic analysis	SmartRoad: a mobile phone based crowd-sourced road sensing system	Medium	
[46]	Traffic analysis	TrafficInfo: Participatory sensing based real-time public transport information service	High	
[47]	Traffic analysis	enviroCar: A Citizen Science Platform for Analyzing and Mapping Crowd-Sourced Car Sensor Data	High	
[48]	Traffic predition	Mobile crowd sensing for traffic prediction in internet of vehicles	Medium	
[49]	Traffic congestion	Cloud-Assisted Mobile Crowd Sensing for Traffic Congestion Control	Low	
[50]	Traffic analysis	Traffic state detection using smartphone based acoustic sensing	Low	
[51]	Traffic predition	RoadCrowd: An approach to road traffic forecasting at junctions using crowd-sourcing and Bayesian model	Medium	
[52]	Parking statistics	Parknet: detecting available parking spots in cities using ultrasonic sensing devices	Low	Parking management
[54]	Vacated parkingspots	Parksense: A smartphone based sensing system for on-street parking	Low	
[55]	Vacated parkingspots	ParkUs: A Novel Vehicle Parking Detection System	Low	
[56]	Automatic parking	Parking Position Detection with Human Cooperation for Automatic Parkin	High	
[57]	Nearest parking spot	SmartPark: a smartphone based system that points drivers to the nearest parking spot	Medium	
[58]	Parking reservation	ParkBid: An Incentive Based Crowdsourced Bidding Service for Parking Reservation	High	
[59]	Vacated parkingspots	ParkGauge: Gauging the Occupancy of Parking Garages with Crowdsensed Parking Characteristics	Low	
[60]	Vacated parkingspots	Crowd-Sensing of Parking Availability with Taxis	High	

[61]	Cracks detection	CrackDetector: Detecting Type and Size of Road Crack with the Smartphone.	Medium	**Ground transportation monitoring**
[62]	Transportatio n infrastructures monitoring	An aggregation and visualization technique for crowd-sourced continuous monitoring of transport infrastructures	Medium	

4.3 Social MCS applications

An account of human powered applications of MCS applications revealed multiple aspects e.g., individuals share sensed information amongst themselves involving recommendations and opinions, life experiences and service/activity suggestions. Several social MCS [63] based applications have been proposed for venue recommendation where the historical location trajectories recorded by mobile devices are leveraged. For example, Y. Zheng et al. proposed a location-history-based recommender system, which uses a particular individual's visit on a geospatial location as their implicit ratings on the location, to predict a particular user's interest in an unvisited location [64]. Another place recommendation system was proposed in [65] to provide a point-of-interests (POI) recommendation service for the rapid growing location-based social networks. In [66], the authors proposed a new system for real-time detection and recommendation of thermal spots. The main idea is to simultaneously aggregate flight information from many paraglider pilots using their location-aware mobile phones. Y. Chon et al. presented CrowdSense@Place (CSP), a framework that exploits a previously untapped resource opportunistically captured images and audio clips from smartphones to link place visits with place categories (e.g., store, restaurant) [67]. CheckInside was introduced by M. Elhamsharyet al. to provide a fine-grained indoor location-based social network. CheckInside exploits the crowd-sensed information collected from users' mobile devices during the check-in operation and knowledge extracted from current LBSNs (location-based social networks) to associate a place with its name and semantic fingerprint [68]. Also, Z. Yu et al. proposed a travel package recommendation system to help users make travel plans by leveraging mobile crowd sourced data [69]. Another venue recommendation application, called SIPF (Social-aware Interesting Place Finding), was proposed in [70] where user's travel experience and social relationship are mainly exploited. An enhanced version of SIPF was also proposed in [71], namely SIPF+. Recently, C Huang el al. presented an unsupervised approach to accurately discover interesting places in a city from location based social sensing applications which collect users' observations of the physical world [72]. CrowdTravel was also recently proposed to provide travel assistance for tourists by crowd intelligence mining [73].

Another example of social application in MCS is the DietSense system [74], where users take pictures of what they eat and share it within a community to compare their eating habits. A classical usage example for this is for a community of diabetics to lookout what other diabetics eat and control their diet or deliver recommendations to others. CrowdMonitor represents also a distinctive example of social MCS application. CrowdMonitor was designed to create coordination mechanisms for interacting and collaborating with the public during emergencies [75].

Table 3. A summary of main social applications for MCS

Ref	Usage	Description	Involvement of the users in the sensing process	Application domain
[64]	Point-of-interests recommendation	Recommending friends and locations based on individual location history	High	**Venue recommendation**
[65]	Point-of-interests recommendation	Exploiting geographical influence for collaborative point-of-interest recommendation	High	
[66]	Thermal spots recommendation	Real-time detection and recommendation of thermal spots by sensing collective behaviors in paragliding	Medium	
[67]	Places characterizing	CrowdSense@Place: Automatically characterizing places with opportunistic crowdsensing using smartphones	Medium	
[68]	Places characterizing	CheckInside: A fine-grained indoor location-based social network.	Medium	
[69]	Travel packages recommendation	Recommending travel packages based on mobile crowdsourced data	High	**Travel assistance**
[70]	Place finding	SIPF : Social-aware Interesting Place Finding	Medium	
[71]	Place finding	SIPF+: social-aware interesting place finding in social sensing applications	Medium	
[73]	Travel recommendation	CrowdTravel: Unsupervised interesting places discovery in location-based social sensing	Medium	
[74]	Diet control	Image browsing, processing, and clustering for participatory sensing: lessons from a DietSense prototype	High	**Medical & Emergency**
[75]	Emergency control	CrowdMonitor: Mobile crowd sensing for assessing physical and digital activities of citizens during emergencies	Medium	

4.4 Behavioral applications

Another outcome of human-powered sensing applications categorized under behavioral domain revealed various interesting aspects. The authors in [76] created social designs using client histories from micro-bloggers and propose models based on conglomeration and scattering. These social approaches are used to find geographic characteristics accumulated from Twitter to study crowd's behavior. In [77], the authors investigated crowd's urban lifestyles and its behavior using Twitter, and propose a system model for a large-scale urban analytics with the location-based social network represented by crowd's temporal behavioral patterns. Wirz et al. in [78] investigated how real-time participatory MCS can be exploited to infer collective behavior patterns and to conclude about community intelligence. In this research, the authors reveal that real-time detection of collective behavior patterns that emerge among the pilots leads to discover regions with ideal thermal characteristics, which can help pilots to extend their flight time and to fly longer distances.

In [79], Bin et al. address human urban mobility/behavior patterns by analyzing the check-in histories of a huge set of LBSN (location-based social organize) clients. An application named EmotionSense was created by capturing the user's emotive, behavioral, and social signals, based on which one's real-time nature can be distinguished. Jia et al. recognized the MCS potential with behaviors perspective in [80]. In this study, authors reference various applications and systems, such as DietSense and BikeNet for healthcare, CenceMe and Co-evolution model for behavior and relationship discovery, PIER for calculating personalized environmental impact and exposure. The authors in [81] developed applications of mobile crowd sensing include emergency behavior pattern and its usefulness.

An application of MCS paradigm in supporting efficient, safe and green mobility in urban environments with behavior perspectives was presented in [82]. They develop CitySensing framework demonstrating the viability of a common crowd-sourcing platform applied to various urban mobility domains. In their MCS research, authors reveal to crowd source diverse information in behavioral domains that are relevant to urban life and mobility (traffic, air quality and citizens' everyday activities). For Crowd-traffic sensing, system detect and report traffic events, road infrastructure, driver behavior and activities, and accidental events. For Air quality sensing, the ExposureSense application sensed air-quality parameters (like temperature, concentration of different particles or gasses in the air). Urban authorities can use such crowd intelligence to improve urban mobility by detecting mobility behaviors and patterns of citizen's/tourists movement. For citizen's behavior pattern sensed using UrbanSense application served as a mobile diary service that detects and stores information about users' environment and mobile interaction by collecting relevant information.

The authors in [83] simulated the sociability behavior of participants in MCS scenarios using sociability profiles for battery power saving. In [84, 85], authors develop predictive models for the discovery of events, communities and knowledge to study behavior patterns. In [86], authors preciously identify behavioral patterns of smartphone/tablet users in which social networking applications were the target platforms to mine behavioral patterns. MCS was employed in [87] to investigate the behavioral pattern with IoT. In [88], Atzori et al. concluded that IoT would have a high impact on potential users' behavior. In [89], Gorlatova et al. analyze a motion dataset and develop an energy allocation algorithm with accessible IoT node solution in order to characterize the energy availability related to particular human behaviors. In [90], Liu et al. monitor the mobility patterns of citizens and visualize data to show development trends in a city's economy and infrastructure specific to resident transport behavior.

In [91], Adeel el al. address how to provide a cost-effective networking service for real-time and delay-tolerant applications in Mobile Urban Sensing System for mobility/behavior patterns. In [92], authors present a MCS system for measuring mental well-being from behavioral indicators in natural everyday settings as primary healthcare e.g. weight loss. In [93], authors present a MCS system for measuring intake via automated tracking of wrist motion in healthcare.

Table 4. A summary of some behavior applications for MCS

Ref	Usage	Description	Application domain
[76]	Geolocation characterizing	Develop social design based on client histories from micro-blogger via Twitter.	Geographical characteristics
[77]	Point-of-interests recommendation	Exploiting urban lifestyle and behavior pattern using Twitter.	Location based social network
[78]	Thermal spots recommendation	Crowds infer collective behavior pattern to conclude community intelligence.	Travelling assistance
[79]	Emotion characterizing	Exploit behavior pattern by analyzing check-in history location based social client	Urban mobility
[80]	Point-of-interests recommendation	Address potential of MCS references such as DietSence, BikeNet, CenseMe, Co-evolution and PIER applications	Healthcare, behavior and relation discovery, environment
[81]	Point-of-interests recommendation	Address emergency behavior pattern and its usefulness	Emergency behavior
[82]	Traffic, air pollution and citizen behavior characteristics	Develop CitySensing framework based on Crowd-traffic, ExposeSence and UrbanSence applications	Urban lifestyle and mobility
[83]	Social characteristics	Simulate social behavior of participants in MCS using their social profile	Power saving for mobile battery
[84, 85]	Point-of-interests recommendation	Develop predictive model for discovery of events, communities and knowledge.	Community behavior
[86]	Point-of-interests recommendation	Mining behavior pattern of smartphone users with social networking application	Social network
[87]	Point-of-interests recommendation	Investigate behavior pattern with MCS in IoT	Behavior pattern with IoT
[88]	Point-of-interests recommendation	Concluded that IoT has high impact on potential user behavior	Social network with IoT
[89]	Energy saving	Develop energy saving algorithm for IoT node selection to characterize energy availability.	Energy saving with IoT
[90]	Point-of-interests recommendation	Monitor citizen mobility pattern to show the development in city economics and infrastructure.	Urban development
[91]	Networking Services	Address how to provide network services for Mobile Urban Sensing System.	Mobile urbanization
[92]	Basic healthcare with weight loss	Develop MCS system for mental well-being for behavior pattern	Healthcare
[93]	Measuring intake in healthcare	MCS system to measure intake via automated tracking of wrist motion in healthcare	Healthcare

5. MCS architecture

Depending on the application, different MCS architectures have been adopted [3, 7, 9, 94,95 and 96]. However, to make it more general, a typical MCS application has three basic levels, according to the provided services: 1) Data sensing and storage; 2) data processing and analytics; 3) application and services. Figure 3 presents the three basic levels of the typical MCS architecture model.

5.1 Data sensing and storage level:

This level refers to the sensing and the storage infrastructures and the involved sensing components. Diverse crowd sensing sources are considered, including mobile sensor devices and Internet applications. For this reason, this level provides a standard data collection and common interface to enable crowd sensing from heterogeneous sources. The storage of the sensing data is another service supported by this level where the sensed data are archived and formatted according to a cohesive presentation. Indeed, due to the huge volume, which might be collected through different sources (e.g. collecting weather information in large city), it will be difficult and inappropriate to use classical data management tools. In addition to the data collection and storage, this level provides privacy protection service for sensing and shared personal data.

5.2 Processing and analytics level:

This level is responsible of data analysis, learning and mining. The collected sensory data are processed to extract and leverage the desired information using data mining and machine learning techniques. Also, extracted data will be filtered to eliminate redundancy and ensure accuracy. Indeed, the processing tasks might take place locally on the mobile device or on the mobile cloud. Furthermore a hybrid processing architecture can be applied with some partitioning between the mobile phone and the cloud.

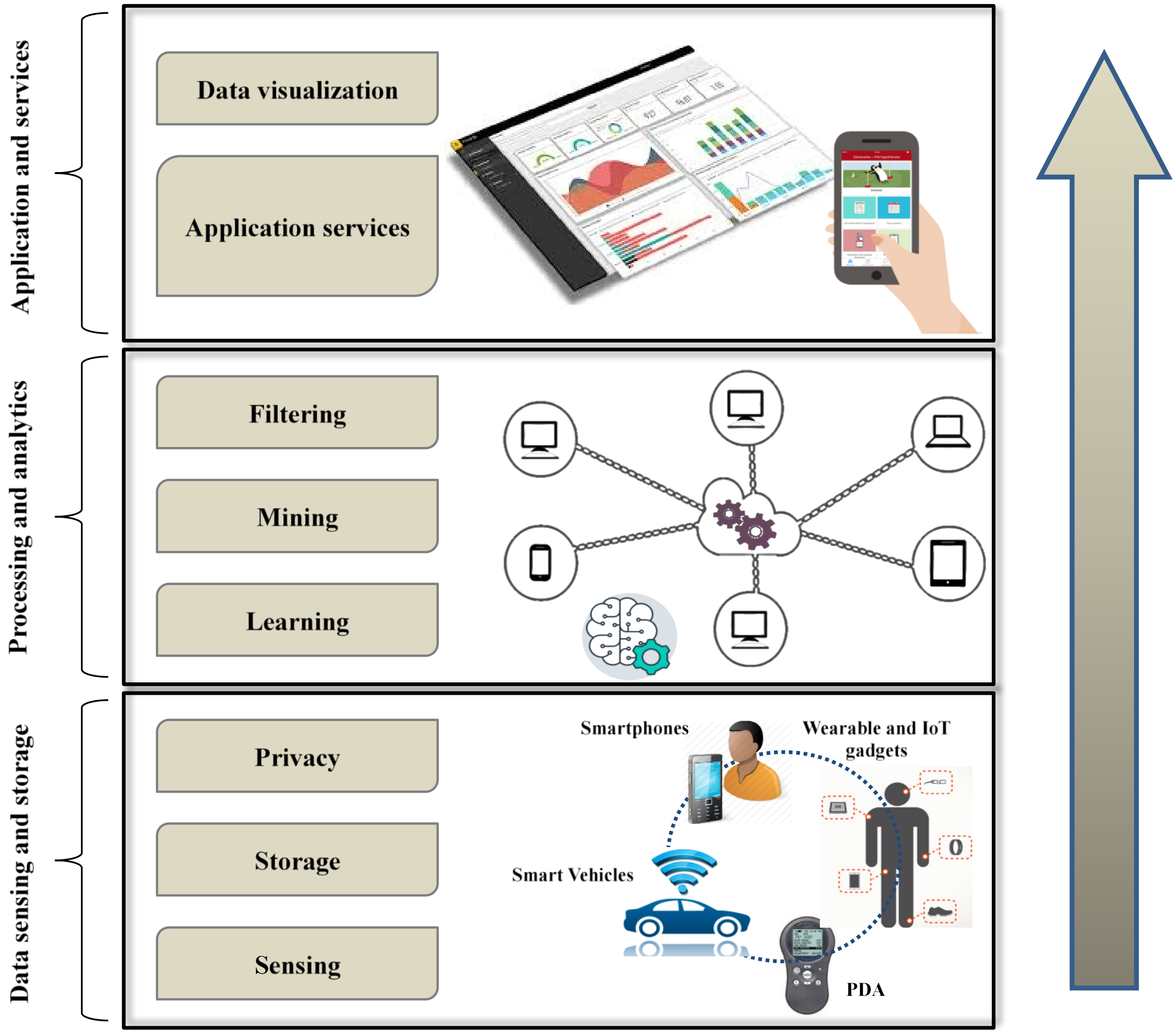

Figure 3. A typical MCS architecture.

This level covers all kinds of MCS applications and services. Also, it defines the user's interfaces and display the services ensuring the presentation of the crowd processed results in a comprehensive format to the final user. In other words, this level is considered as an interface between the backend crowd sensing platform and the users.

MCS architecture can be also divided, according to the interacting entities, into three main components: the server, the mobile providers and the clients. The server component represents a centralized platform which schedules and attributes sensing tasks to be executed on the individual's mobile platforms. Also, the server accepts task requests from clients and then forward them to mobile provider according to the established schedule. The mobile providers represent mobile platforms which participate to the crowd sensing process to provide the sensing data requested by the clients. The clients designate the end users (organization or group of users) which leverage the mobile crowd sensing system to collect and sense data from different mobile devices (e.g., smart phones and PDAs). The communication between all these components occurs through the network. Figure 4, illustrates the MCS architecture according to the involved entities.

Based on the data collecteing and dissemination approach, data pre-processing and task allocation model, MCS architectures can be also classified into centralized or decentralized. Indeed, in the centralized MCS architecture, a central unit takes in charge the management of the data sensing and the sending process. In the other side, the decentralized MCS architecture enables users to fully control their own personal data (e.g., decide with whom they are going to share them and when), with the risk however of acquiring potentially low quality data.

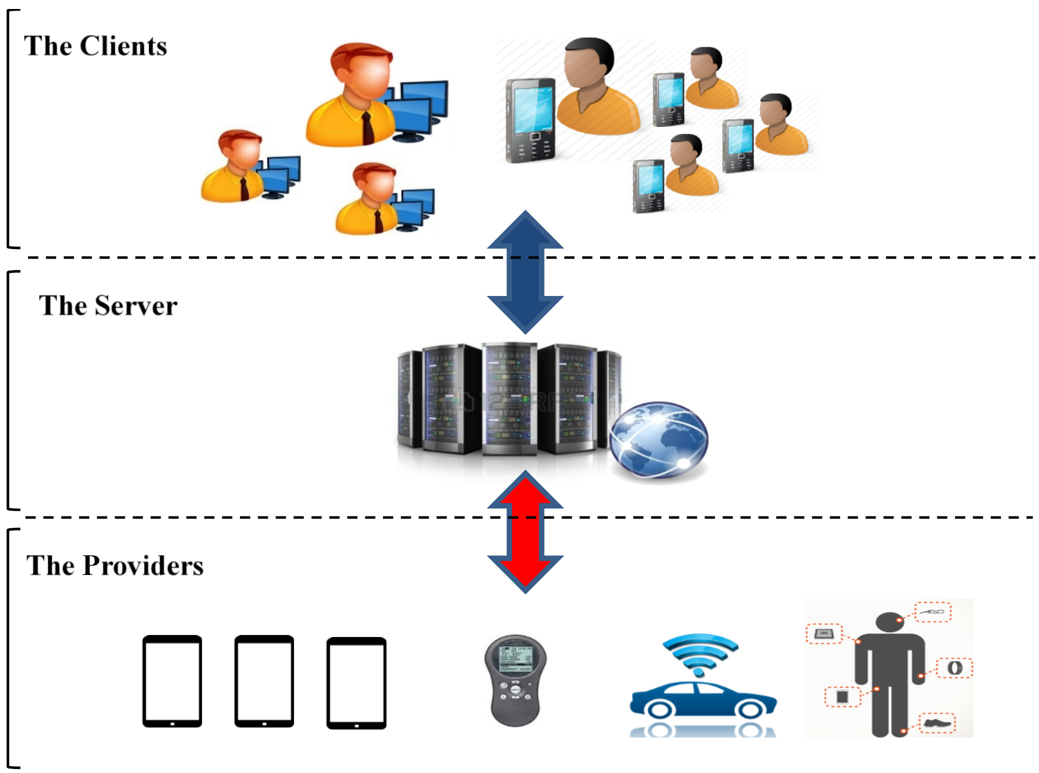

Figure 4. MCS architecture according to the involved entities.

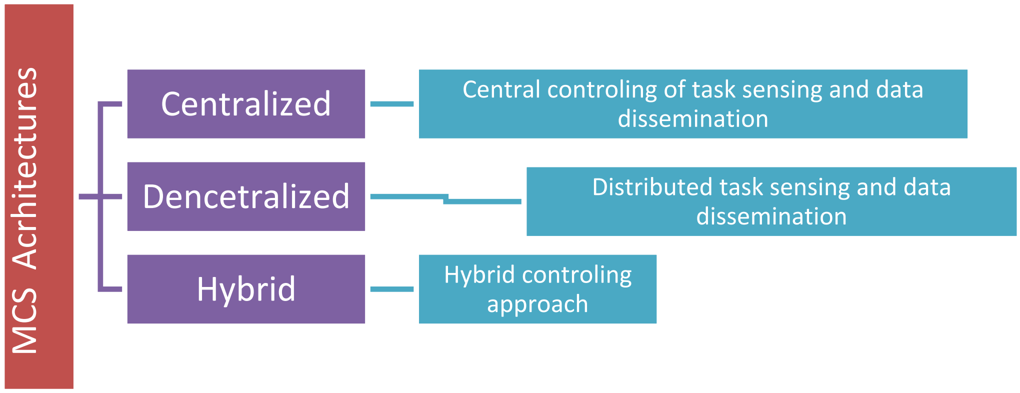

Figure 5. MCS architecture according to the centralized/decentralized control.

6. Challenges and solutions

The unique characteristics of MCS have introduced numerous advantages and benefits as well as several challenges and research opportunities. Indeed, implementing MCS in the real world is complex and can bring several problems related to security and the privacy, human involvement and collaboration, data accuracy, delivery, redundancy and quality. In this section, we provide a general overview of the main MCS challenges and prominent relevant solutions from the literature.

6.1 Human sensing involvement

Integrating human volunteers in the MCS process (e.g., data sensing and gathering, sharing information) represents a real challenge. Indeed, incentive mechanisms are highly needed to incite the human participation and keep the users engaged. Also, managing the human interactions, the event coverage, the group sensing and the task allocation are important points that need to be addressed.

- **Incentive mechanisms:**

Most of MCS applications require voluntary participation. However, contributing to the crowd sensing process is a resource consuming task (e.g. battery and computing power). Also, in most cases, volunteers have to share private information about themselves (i.e., data with tag location) which might expose them to several security threats. Therefore, MCS would be not attractive for users unless they receive sufficient recompenses to pay back the potential resource consumption and privacy breach. Indeed, without efficient incentives, the users may not participate in such applications. It is a challenge to attract appropriate users and keep them involved while sensing the measurements on the smart phone. Different incentive strategies can be applied to attracting users. Most of these strategies are based on financial rewards or ranking and social recognition. Also, incentive strategies can be based on attention-grabbing task (gamification), enjoyment and altruism services.

Several research works, which investigate the incentive issues in MCS, have been proposed in the literature. In the following, we give a short survey of these incentive solutions based on the adopted rewarding strategie.

Ranking and social reputation based incevtive mechanisms

SenseMart [97], represents one of the first research works that addressed the use of reputation based incentive mechanisms to facilitate the exchange of sensing data among users (as in a marketplace). APISENSE represents another ranking based incentive platform that encourages scientists and participants to contribute to the sensing experiments. Scientist incentives include the modular integration of a wide variety of features they can compose upon their need, while the participant incentives deal with privacy and rewarding mechanisms that can be offered in order to catalyze the collection of datasets [98]. A general privacy-preserving framework for incentivizing the crowd sensing, named BidGuard, was proposed in [99]. The authors considered both the bid privacy of the smartphone users and the social cost to design an efficient incentive mechanism which achieves better computational efficiency, individual rationality, truthfulness, differential privacy and approximate social cost minimization. Recently, G. Yang et al. introduced a novel approach, called the social incentive mechanism, which, surprisingly, incentivizes the social friends of the participants who perform the sensing tasks. The basic idea is to leverage the social ties among the participants to promote global cooperation [100]. Similarly to [100], Chen, Y et al. proposed to incorporate sensing platform and social network applications, which already have large user bases to build a three-layer network model. Thus, the sensing platform can be publicized promptly in large scale, and provide long-term guarantees of data sources [101]. Luo, T. et al. provided an exposition of design principles of six incentive mechanisms, drawing special attention to the sustainability issue. The authors covered three primary classes of incentive mechanisms: auctions, lotteries, and trust and reputation systems, as well as three other frameworks of promising potential: bargaining games, contract theory, and market-driven mechanisms [102]. Guo, B. et al proposed a novel MCS incentive mechanism called TaskMe. The main idea is to leverage an LBSN (location-based social network)-powered model for dynamic budgeting and proper worker selection, and to improve the sensing quality by the use of a combination of multi-facet quality measurements and a multi-payment-enhanced reverse auction scheme [103].

Financial based incetive mechanisms

In order to stimulate the user participation, J.S Lee et al. designed a novel Reverse Auction based Dynamic Price (RADP) incentive mechanism, where the users can sell their sensing data to a service provider with users' claimed bid prices [104]. A comparative study was presented in [105] to analyze different incentive mechanisms for motivation and collaboration of smartphone users. The authors also introduced two rewarding models for the data acquisition and the distributed computing. Q Li et al. addressed the security aspect in the incentive mechanism and proposed two privacy-aware incentive schemes. The proposed schemes allow each mobile user to earn credits by contributing data without leaking information, and ensure at the same time that the dishonest users cannot abuse the system to earn unlimited amount of credits [106]. J Sun et al. investigated the negligence of the data quality and privacy during the incentive mechanism design and proposed a behavior based incentive mechanism which maximizes the high quality of sensing data under the budget constraint [107]. iMac was introduced in [108] for incentive crowd sensing where the users are stimulated to truthfully disclose their real costs, preventing thus user misreporting cost (different from the real cost) and overpayment. L.G. Jaimes et al. proposed SPREAD, an incentive crowd sensing mechanism designed to obtain the lowest cost samples that are best distributed to cover the area of interest within a fixed budget [109]. In [110], the authors presented a reverse auction mechanism as an efficient way to offer incentives to the users by allowing them to determine their own price for the data they provide, but also as a way to motivate them to submit the data in better quality [110]. In [111], the authors incorporated the consideration of data quality into the design of incentive mechanism for crowd sensing, and propose to pay the participants as how well they do, to motivate the rational participants to perform data sensing efficiently [111]. INCEPTION, a novel MCS system framework that integrates an incentive, a data aggregation, and a data perturbation mechanism was proposed in [112]. The main idea is to select the workers who are more likely to provide reliable data, and compensates their costs for both sensing and privacy leakage. Yang, D. et al. designed incentive mechanisms based on two system models: the crowd source-centric model where the crowd source provides a reward shared by participating users, and the user-centric model where the users have more control over the payment they will receive [113].

Gamification based incetive mechanisms

X. Liu et al. proposed an incentive game based on an evolutionary model for the crowd sensing networks. Through the evolutionary game model, the manager can select an optimal price to facilitate the system to reach equilibrium state quickly, and get the number of participants involved in the game [114]. Chen, X. et al. designed an efficient and truthful incentive mechanism to encourage the users to participate. To address the challenge, the authors proposed a novel truthful online auction mechanism that can efficiently learn to make irreversible online decisions on winner selections for new MCS systems without requiring previous knowledge of users [115].

Table 5. Summary of solutions for human MCS involvement

Proposed solutions		Challenges handled
Solution description	**Rewarding strategie**	
SenseMart: Sensing Data Market that stimulates user participation [97]	Reputation rankings	Incentive mechanism
RADP: Reverse Auction based Dynamic Price mechanism [104]	Financial rewards	
Rewarding models for data acquisition and distributed computing [105]	Financial rewards	
Privacy based incentive schemes [106]	Financial rewards	
APISENSE: an incentive platform for scientists, and participants [98]	Participant rankings, involvement badges	
BBS: A behavior based incentive mechanism with budget constraints[107]	Financial rewards	
iMac: incentive mechanism to prevent overpayment [108]	Financial rewards	
SPREAD: incentive assignment mechanism To Acquire Better Representative Samples [109]	Financial rewards	
Privacy-respecting auctions as incentive mechanisms in the mobile crowd sensing [110]	Financial rewards	
A Quality Based Incentive Mechanism for Crowd sensing [111]	Financial rewards	
INCEPTION: Incentivizing Privacy-Preserving Data Aggregation for MCS [112]	Financial rewards	
An incentive game based evolutionary model for crowd sensing networks [114]	Gamification	
Source-centric and user-centric based incentive mechanism for MCS [113]	Financial rewards	
BidGuard:A Framework for Privacy-Preserving Crowd sensing Incentive Mechanisms [99]	Ranking and social recognition	
Promoting cooperation by the social incentive mechanism in the mobile crowd sensing [100]	Ranking and social recognition	
A three-layer incentive framework for the mobile crowd sensing [101]	Ranking and social recognition	
A Truthful Incentive Mechanism for Online Recruitment [115]	Gamification	
Sustainable Incentives designs for Mobile Crowd sensing [102]	Bargaining games, reputation rankings and financial rewards	
TaskMe: dynamic and quality-enhanced incentive mechanism [103]	Social recognition and financial rewards	
ESWM: Expected Social Welfare Maximizing [116]	Financial rewards	
Practical Incentive Mechanisms for IoT-Based Mobile Crowdsensing Systems [117]	Financial rewards	
HySense: A Hybrid Mobile CrowdSensing Framework for Sensing Opportunities Compensation under Dynamic Coverage Constraint [118]	Financial rewards	
RIT: Robust Incentive Tree Design for Mobile Crowdsensing [119]	Financial rewards	
Geo-QTI: A quality aware truthful incentive mechanism for cyber–physical enabled Geographic crowdsensing [120]	Gamification and financial rewards	
A QoS-Aware Online Incentive Mechanism for Mobile	Financial rewards	

Crowd Sensing [121]		
Privacy-Aware Incentive Mechanism for Mobile Crowd Sensing [122]	Financial rewards	
TAFA: an auction-based incentive mechanism for crowdsourcing [123]	Financial rewards	
FIMI: A Constant Frugal Incentive Mechanism for Time Window Coverage in Mobile Crowdsensing [124]	Financial rewards	
TSIA: Time-sensitive incentive-aware mechanism for mobile opportunistic crowdsensing data collection [125]	Bargaining games	
An Incentive Mechanism for Crowdsensing Markets with Multiple Crowdsourcers [126]	Gamification and financial rewards	
PIE: A personalized incentive for location-aware mobile crowd sensing [127]	Financial rewards	
A Double Auction Mechanism for Mobile Crowd Sensing with Data Reuse [128]	Financial rewards	
An iterative incentive mechanism design for crowd sensing using best response dynamics [129]	Gamification and financial rewards	
Solution description	**Selection/Filter criteria**	Task allocation
Dynamic data driven crowd sensing task assignment [130]	Region coverage	
Location Privacy-Preserving Task Allocation for Mobile Crowdsensing [141]	User privacy	
Recruitment framework for participatory sensing data collections [131]	Region coverage and user behavior	
CrowdRecruiter: participant selection framework for MCS [137]	Sensing cost and region coverage	
Optimal Allocation of Location Dependent Tasks in Crowdsensing [138]	Processing and sensing cost	
CCS-TA: Quality-guaranteed online task allocation in compressive crowd sensing [132]	Region coverage	
Multi-task assignment for crowd sensing [139]	Processing and sensing cost	
iCrowd: Near-optimal task allocation for piggyback crowd sensing [133]	Sensing cost and region coverage	
Budget-feasible online incentive mechanisms for crowdsourcing tasks truthfully [140]	Sensing cost and user privacy	
Real-time task assignment in hyper local spatial crowdsourcing under budget constraints [134]	Region coverage (spatiotemporal)	
Activecrowd: A framework for optimized multitask allocation in MCS [135]	Region coverage (spatiotemporal)	
Distributed auction schemes for task allocation and scheduling [136]	Sensing cost and region coverage	
Mew: A Plug-n-Play Framework for Task Allocation in Mobile Crowdsensing [142]	User privacy	
Solution description	**Grouping strategie**	Participant interactions
Virtual team formation approach [143]	Request based grouping	
Community-aware smartphone sensing systems [144]	User skills and attributes based grouping	
GroupMe: Supporting Group Formation with Mobile Sensing [145]	Social graph mining	
MobiGroup: Mobil group activity organization in MCS [146]	Activity based grouping	

- **Task allocation:**

To ensure efficient crowd sensing, task assignment approaches are applied to select a set of qualified individuals to perform the sensing tasks. Indeed, participant selection introduces more challenges in the MCS and can have impact on the efficiency and quality of the sensing results. Several criteria are used to filter the inappropriate participants such as the available device competencies, region coverage (e.g. selecting sensing devices situated in the desired monitoring region), sensing cost and participant privacy. Commonly, a task assignment framework includes three main entities: 1. Participants which represent individuals who use a sensor to obtain or measure the required data about a subject of interest. 2. Applications or end users, which are the entities that request data through tasks and then utilize the information acquired by the participants. 3. Tasking entities which are responsible for distribution of tasks to participants who meet the requirements of applications [130].

Based on the user selection criteria we summarize most important proposed task allocation approaches as follow:

<u>Spatiotemporal based task allocation solutions</u>

Reddy S. et al. discussed the development of a recruitment framework to enable the organizers to identify the well-suited participants for data collections based on geographic and temporal availability as well as participation habits [131]. Pournajaf, L. et al. proposed a novel model for the spatial task assignment in the MCS that uses a dynamic and adaptive data driven scheme to assign moving participants with uncertain trajectories to sensing tasks, in a near-optimal manner [130]. Wang, L. et al. proposed a novel framework called CCS-TA, combining the state-of-the-art compressive sensing, Bayesian inference, and active learning techniques, to dynamically select a minimum number of sub-areas for sensing task allocation in each sensing cycle, while deducing the missing data of non allocated sub-areas under probabilistic data accuracy guarantee [132]. Xiong, H.et al. introduced iCrowd, a generic MCS task allocation framework operating with the energy-efficient Piggyback Crowd sensing task model to optimize the MCS task allocation with different incentives and k-depth coverage objectives/constraints [133]. To, H. et al. introduced a task allocation framework in which only the workers who are already within the spatiotemporal vicinity of a task are eligible candidates to report data, e.g., the precipitation level at their area and time. In this setting, a subset of candidate workers whose size is constrained by a predefined budget can be activated to perform tasks [134]. Recently, Guo, B. et al. studied the worker selection problem under multi-task MCS environments and have identified two common situations: intentional-movement-based selection for time-sensitive tasks and unintentional-movement-based selection for delay-tolerant tasks. The optimal goal for the two situations varies and the authors proposed two greedy-enhanced genetic algorithms GGA-I, GGA-U to address them [135]. Also, Duan, Z. et al. studied the joint problem of sensing task assignment and scheduling while considering partial fulfillment, attribute diversity, and price diversity. Furthermore, the authors proposed two distributed auction schemes, cost-preferred auction scheme (CPAS) and time schedule-preferred auction scheme (TPAS) which optimize the sensing task's allocation efficiency, mobile user's working time utilization and utility, and truthfulness [136].

Sensing const and device competencies

Crowd Recruiter represents another proposed task allocation framework which operates on top of energy-efficient Piggyback Crowd sensing (PCS) task model and minimizes the incentive payments by selecting a small number of participants while still satisfying probabilistic coverage constraint [137]. He, S. et al. defined the task allocation problem as NP-hard and designed a pricing mechanism based on bargaining theory, in which the price of each task is determined by the performing cost and the market demand [138]. In [139], the authors proposed two task allocation algorithms: an oFfline Task Assignment (FTA) algorithm and an oNline Task Assignment (NTA) algorithm. Both of the algorithms adopt a greedy task assignment strategy to achieve the minimum average of the task carrying out. Zhao, D et al designed two online task assignment mechanisms, OMZ and OMG, satisfying six desirable properties: computational efficiency, individual rationality, budget feasibility, truthfulness, consumer sovereignty and constant competitiveness [140].

User privacy

There are some preliminary studies on task allocation design for MCS based on user privacy. WANG Leye et al. proposed a location privacy-preserving task allocation framework with geoobfuscation to protect the users' locations during the task assignments [141]. Bajaj, G et al. proposed Mew, which offers plug-n-play functionality for implementing the custom task allocation algorithms to allow developers to reach out to the required set of participants while solving privacy challenge associated with MCS application in a black-box manner [142].

- **Participant interactions:**

Managing participant interactions represents an important step for the optimal crowd sensing process. Indeed, grouping users, facilitates the interaction among them and might enhance the data quality in MCS. However, managing user's interactions is a complex task that was neglected in most existing crowd sensing systems. Only few research works addressed this issue [143].One of first research works that addressed the group formation challenge in MCS was presented in [143]. The authors proposed a virtual team formation approach that employs an expertise matching mechanism and discovered social relationships. Lane, N. D. et al. also pointed out the importance of participants interactions and group formation in designing better equip sensing systems. The authors also exposed the need of automated methods to identify which user interactions and ties are the most salient to the operation of the sensing system [144]. Guo, B. et al. proposed another participants grouping approach called GroupMe, which facilitates the activity group initiation based on mobile sensing and social graph mining [145].A group-aware mobile crowd sensing system called MobiGroup was proposed in [146], which supports group activity organization in real world settings. The authors present a formal concept model to characterize group activities and classify them into four organizational stages. Also an intelligent approach to support group activity preparation was introduced.

6.2 Data quality issues

Ensuring high data quality without redundancy and inconsistency represents a big challenge for MCS systems. Indeed, data quality, in terms of accuracy, latency, completeness and sparsity, is highly impacted by MCS characteristics such as participant mobility, device owners' preferences and the type of sensor data each one can produce and the variation in the communication channels.

- **Redundant and low quality data :**

MCS involves a large amount of individual volunteer in the sensing process which may lead to data redundancy. Therefore, it is imperative to efficiently select data from multiple available sources. Indeed, several sensing sources may collect the same data with different quality levels due to the variation of the sensing conditions. Thus, applying data selection and filtering approach is needed to reject low-quality or irrelevant data. To exclude the negative impact of abnormal or low-quality data in crowd sensing, Ding et al. introduced a data cleansing-based robust spectrum sensing algorithm [147]. Messaoud R. M. et al proposed another selection scheme for participatory sensing tasks, named QEMSS, to select, among all participants in the sensing campaigns, the subset of users who maximizes the quality of information of non-redundant information while minimizing the overall energy consumption [148]. Marjanović, M. et al. presented a framework for Green MCS (G-MCS) which utilizes a quality-driven sensor management function to continuously select the k-best sensors for a predefined sensing task. In particular, it removes redundant sensor activity while satisfies sensing coverage requirements and sensing quality [149]. PicPick, is another data selection approach which aims to eliminate data redundancy and reduce the network overhead. PicPick first presents a multifaceted task model that allows sensing task specification for variable data. A pyramid tree (PTree) method is further proposed to select an optimal set of data from data streams based on multi-dimensional constraints [150]. Recently, Meng, C. et al. developed an integrated framework to estimate the true values of entities from redundant and sparse data in crowd sensing applications [151]. The authors proposed an effective algorithm to infer the "missing" observations for each entity, and aggregate both user-contributed and deducted observations to discover the true values of entities.

- **Data accuracy and completeness:**

The incompleteness and correctness of sensory data pose several challenging issues for efficient MCS process. Indeed, only in an ideal environment, participants provide accurate and complete sensing readings. Kurasawa et al. pointed out that the data collected by crowd usually include considerable missing values in practical crowd-sensing systems. They proposed a method to estimate missing values using a recursive regression model [152]. several research progresses in missing data inference algorithms, such as compressive sensing, could facilitate MCS to achieve high inferred data quality [153], [154], [155], [156]. To address the problem of low quality, misleading and inaccurate data, Yang, H. et al. proposed to use a reputation management approach to classify the gathered data and provide useful information for campaign organizers and data analysts to facilitate their decisions [157]. Recently, Cheng L. et al. proposed Deco, a general framework to detect false values for crowd-sensing in the presence of missing data. By applying a tailored spatio-temporal compressive sensing technique, Deco is able to accurately detect the false data and estimate both false and missing values for data correction [158]. Santosh K. et al. proposed an intelligent decision computing based paradigm for crowd monitoring in the smart city. In the intelligent computing based framework, the optimization algorithm is applied to compute the feature of crowd motion and measure the correlation between agents based motion model and the crowd data using extended Kalman filtering approach and KL-divergence technique [159].

6.3 Security and privacy

Alongside the data quality and human involvement concerns, security is rated as a top challenge issue. As MCS applications involve data collection across a large number of human participants, several security threats may occur targeting mainly data privacy and integrity. Therefore, it is imperative to ensure data integrity and privacy without restraining MCS applications.

6.3.1 Threat model and security attacks in MCS

Degrading the MCS service level, crashing the system or stealing privacy data are the main objectives of an attacker. Also, MCS can be targeted by an internal attacker which aims to extract secrets or obtain rewards with less sensing efforts. On the other hand, more complex attackers can apply machine learning techniques to perform attacks with selected policy and generate then dangerous threats which can overcome the MCS security defenses. In the following, we briefly review some significant types of threats in MCS.

Faked sensing attacks: Under-sensing or faked sensing reports can be occasionally submitted by selfish mobile users to save sensing efforts and protect privacy.

Malwares: Resource constrained mobile users are particularly vulnerable to malwares. Indeed, malwares such as spy tools, viruses or worms seriously threaten MCS with the network performance degradation, economic loss and privacy leakage.

Spoofing attacks: In this kind of attacks, the identity of a legitimate mobile device or an access point can be used by the attacker to illegally access the MCS system. Also, other attacks, such as man-in-the-middle and DoS attacks, can be performed based on the spoofed identity.

Sybil attacks: A large number of different user identities can be used by a Sybil user to send sensing reports and influence the sensing result made by the majority-based MCS server.

Privacy leakage: User privacy must be protected by MCS servers particularly the user locations and the personal information. Indeed, privacy information can be stolen by rogue users from transmission processes or cloud resources which may discourage the other mobile users from participating to the MCS tasks.

DoS attack: This attack targets mainly the MCS services in order to reduce the performing level and exhaust the MCS server resources.

Jamming: the main objective is to interrupt the ongoing transmission of the sensing data by injecting faked or replay signals. To overcome the anti-jamming technics, the attacker can use multiple jamming power and frequency according to the transmission status.

6.3.2 MCS security issues and countermeasures

- **Data privacy:**

The sensing data collected by mobile devices may inadvertently reveal personal information about the mobile users, including identity, location, habit, health status, daily route, and political affiliation. Furthermore, the more tasks mobile users engaged in and the richer data they contribute to, the higher possibility that their sensitive information is disclosed [160]. Several research works addressed the privacy problem in MCS applications. A popular approach for preserving the privacy of the data is that of anonymization which removes any identifying information from the sensor data before sharing it with a third party [3]. However, privacy attack can be lanced based on other sensitive information like GPS position. Cryptographic solutions represent another alternative to prevent privacy attacks, though, this kind of security approaches are compute intensive and unsuitable for the resource limited MCS devices. To effectively preserve the privacy, not only methodology efforts, but also systematic studies are needed. In other words, a privacy-aware architecture should be provided to support the development of MCS applications [7]. Cornelius, C. et al. proposed one of the first privacy-aware architectures for MCS named AnonySense. AnonySense allows applications to submit sensing tasks that will be distributed across anonymous participating mobile devices based on a stringent threat model that adopts minimal trust assumptions [161]. Konidala, D. M. et al. focused on both authentication and privacy aspects and proposed an anonymous authentication of visitor's protocol that protects the privacy of visitors even while collecting their details, preferences and location coordinates [162]. Krontiris, I. et al. suggested a mobile node discovering mechanism that corresponds to range queries about a geographical area. This mechanism enables mobile users to protect their location privacy, according to their own preferences and enforce access policies to their own data [163]. SPPEAR, a comprehensive, secure and privacy-preserving architecture, was proposed in [164] to address security and privacy concerns in participatory sensing systems. SPPEAR guarantees the user non-identifiability and offers strong privacy protection, limits participation to legitimate users in a fully accountable manner and efficiently shuns out offending users without, necessarily, revealing their identity [164]. Another privacy solution was introduced in [165] were the authors proposed a mobile sensing platform that protects the anonymity of both data requesters and producers, while enabling at the same time the incorporation of trust frameworks, incentive mechanisms and privacy-respecting reputation schemes. Miao, C. et al. proposed a novel cloud-enabled privacy-preserving truth discovery (PPTD) framework for crowd sensing systems, which can achieve the protection of not only users' sensory data but also their reliability scores derived by the truth discovery approaches [166].Wu, X. et al. presented a privacy preserving RSS map generation scheme for crowd sensing networks called PRESM. To protect the privacy of user traces, the authors exploit the compressive sensing technique to sample and compress RSS (Received Signal Strength) values along each road segment, which removes the temporal and concrete location information of each participant [167]. PPCS, a novel Privacy Preserving Compressive Sensing scheme, was introduced by Kong, L. et al. to preserve the user privacy. The main idea is to perturb a trajectory with several other trajectories while maintaining the homomorphic obfuscation property for compressive sensing. Under PPCS, adversaries can only capture the encrypted data [168].Shin, M. et al. proposed and evaluate a novel spatiotemporal blurring mechanism based on tessellation and clustering to protect users' privacy while reporting context. The proposed technique employs a notion of probabilistic *k*-anonymity; it allows users to perform local blurring of reports efficiently without an online anonymization server before the data are sent to the system [169]. The privacy of trajectory information was also addressed in [170] where the authors proposed a participant coordination framework, which allows the system server to provide optimal QoI (Quality of Information) for sensing tasks without knowing the trajectories of participants. A comprehensive security and privacy-preserving architecture was proposed in [164]. The main idea is to extend the SPPEAR protocol to optimize the user privacy while supporting user incentive mechanisms. INCEPTION, represents a novel MCS system framework that integrates an incentive, a data aggregation, and a data perturbation mechanism. Specifically, its incentive mechanism selects workers who are more likely to provide reliable data, and compensates their costs for both sensing and privacy leakage. Data perturbation mechanism ensures satisfactory protection for workers' privacy and desirable accuracy for the final perturbed results [112]. Recently, Ni, J. et al. proposed a privacy-preserving mobile crowd sensing framework (PPMC) for location-based applications to balance the tradeoff between privacy preservation and task allocation. In PPMC, the authors developed a matrix-based location matching mechanism for the service provider to achieve location-based task allocation without disclosing the location of mobile users and the sensing area of tasks [172]. Nasir R. et al. proposed a privacy-preserving image retrieval for mobile devices with deep features on the cloud. The authors proposed to represent images with hash codes, which is a compressed representation of deep convolutional features using deep auto-encoder on the cloud. To ensure user's privacy, the image is first encrypted using a light-weight encryption algorithm on mobile device prior to offloading it to the cloud for features extraction [173].

- **Data integrity:**

Data integrity represents another security aspect which must be addressed to ensure the integrity of sensed data from individual's smart phones. Only few research works focused on the data integrity problem in MCS applications and the field remains undertreated. Dua A. *et al.* proposed and implemented a trusted platform module (TPM), which is a micro-controller embedded within each mobile device, to attest the integrity of the sensor readings. However, TPM chips are not yet widely adopted in mobile devices

[174].Xu, J. et al investigated truthful incentive mechanisms for time window dependent tasks in the mobile crowd sensing based on strong requirement of data integrity [175]. Multidisciplinary approaches to achieve efficient and trustworthy eHealth monitoring systems was introduced in [176]. The authors also proposed a light-weight security mechanism for eHealth monitoring, to ensure authenticity, confidentiality, and integrity of medical data collected from patients. To address the privacy and data integrity problems, Zhang, L. et al. proposed an efficient data aggregation approach by which an untrusted aggregator in mobile sensing can collect the statistics over the data contributed by multiple mobile users, while supporting privacy preservation of each user and data integrity verification. In this approach, information hiding and homomorphic encryption are applied to guarantee the data privacy of mobile users [177]. Yadav, K. et al. Introduced Human Sensors, an architecture of crowd sensing testbed for capturing and processing events affecting citizens in cities in India. The authors checked the integrity and the authenticity of a report by comparing it to other reports collected from independent participants [178]. Gilbert, P. et al. proposed a trustworthiness model which focuses on data integrity (for data coming from automatic readings from devices), data correctness, and quality. User's contributions are compared to those provided by local authoritative data sources, certified by the data provenance micro service [179]. A novel data aggregation protocol in the crowd sensing system was introduced in [180], to protect the data integrity and achieve authentication and traceability by leveraging the aggregate signature. Also, Chen, J. et al. proposed a novel private data aggregation scheme to address secure data-integrity verification problem while taking into account the security vulnerability of limited data range in MCS applications [181].

- **Data authentication:**

Authenticating the identity of the MCS participants represents an important security issue which contributes to prevent several security threats such as spoofing and Sybil attacks. The identity authentication involves confirming the legitimate identity of the users to obtain authorization for accessing the MCS system. Konidala, D. M. et al. addressed the authentification issue in MCS and introduced an anonymous authentication algorithm to authenticate the identity of the visitor without revealing his/her identity. The fundamental idea is to interact with the visitor using a pseudonym instead of his/her true identity [143]. Based on a similar concept, Ma, P. et al. proposed a pseudonym based anonymous identity authentication mechanism for MCS. The introduced solution contributes to the privacy protection of the authentication process by the means of pseudonym. Also, the authors proposed to combine the Public Key Infrastructure (PKI) and the Combined Public Key (CPK) technology for key and certificate management to solve the problem of the large-scale key management [182]. An enhanced secure certificateless privacy-preserving verifiable data authentication scheme for mobile crowd sensing, named EPDA, was proposed by Liu, J.et al. The proposed scheme provides unconditional anonymous data authentication service for mobile crowd sensing, by deploying an improved certificateless ring signature as the cryptogram essential, in which the big sensing data should be signed by one of the legitimate members in a specific group and could be verified without exposing the actual identity of the participant [183]. Another anonymous authentication scheme was presented In [184]. It provides anonymous authentication to the users who share their important data to any third part. An original authentication strategy was introduced recently by Shi, C. et al. where the unique physical features of WiFi signals in the daily activities of mobile users is captured to identify the mobile users. More specifically, the system extracts 6 time domain features, such as maximum, minimum and skewness, and 3 frequency domain features, including spectrogram energy, percentile frequency component and spectrogram energy difference, from both of the amplitude and the phase of the channel responses of the WiFi signals [185].

- **Data reliability:**

Ensuring the data reliability of the participants' sensed data in crowd sensing is a crucial security issue, since malicious users can submit false data to earn money without executing the actual task. Therefore, there is a need for mechanisms to efficiently validate the collected data. However, the sensing measurements are highly dependent on context; therefore, it is challenging to validate each and every sensed data point of each participant. To handle this issue, several research works are proposed to validate the location associated with the sensed data point in order to achieve a certain degree of reliability on the sensed data. However, this kind of solution is confronted to a major challenge which is the location validation of the data points in a scalable and cost-effective way without help from the wireless carrier. Some traditional approaches have been proposed to ensure reliability on participants' location data such as tasks duplication among multiple participants or using Trusted Platform Modules (TPM) [186]. However, these solutions are usually not recommended due to the introduced cost (installing TPM modules on every smart phone) and feasibility. Another solution to verify the reliability on participants' location data is to exploit the location verification mechanisms [187, 188]. However, more support infrastructures are required and user phones may suffer from significant overhead.

Instead of using data location to garantee the reliability of the sensed data, another approache mainly, based on data mining techniques, aims to discover the ground truth by analyzing the noisy and possibly conflicting MCS data (sometimes taking workers into account as well). Wang et al. used the Expectation-Maximization (EM) algorithm to find the maximum likelihood estimate (MLE) of the probability that a given binary MCS measurement is true [189]. Davami and Sukthankar combined multiple trust-based data fusion techniques using AdaBoost, a machine learning algorithm, to predict whether a parking lot is occupied, based on the crowdsourced user reports [190]. Gisdakis et al. proposed SHIELD to perform outlier detection in the presence of compromised sensing devices, but it requires a large amount of data to train the complex machine learning model [191].

Recently, an original new solution for data reliability was proposed by Li, D. et al. The authors introduced a new cross validation approach into MCS. This approach does not mean comparing a piece of data (contributed by a worker as in the MCS context) against another piece of data (contributed by another worker), which is similar to the approach used in the machine learning and data mining literature. Instead, the new proposed cross validation approach means subjecting the crowd sensed data to a group of crowdworkers who did not contribute to the original MCS data to seek their verification, for the purpose of reshaping or "grooming" the original sensed data toward the ground truth [192].

7. Conclusion

Mobile crowd sensing represents one of the most impactful technologies which will transform radically several sectors of our economy, including environmental monitoring and transportation, business, healthcare and social networks. MCS exploits the sensor's smartphones and the mobility of participants to sense their surroundings, instead of deploying static and expensive sensor network. Moreover, existing communication infrastructures (e.g., 3G, Wi-Fi etc.) are used by MCS applications, to collect data from mobile phones scattered in the monitoring field. MCS will bring promising opportunities, along with new challenges.In this paper, we addressed the mobile crowd sensing concept and presented its main features and advantages, architectures and application domains. Also, we have identified the main MCS challenges and gave an overview on the recent mobile crowd sensing strategies and solutions.

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- A comprehensive review of mobile crowd sensing is presented
- A taxonomy of mobile crowd sensing is devised based on various factors
- Emerging mobile crowd sensing applications are categorized and classified
- An architecture of mobile crowd sensing is described based on the provided services and the interacting entities
- The core challenges of mobile crowd sensing are identified and highlighted