A Survey of Mobile Crowdsensing Techniques: A Critical Component for The Internet of Things

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***Abstract*—Mobile crowdsensing serves as a critical building block for the emerging Internet of Things (IoT) applications. However, the sensing devices continuously generate a large amount of data, which consumes much resources (e.g., bandwidth, energy and storage), and may sacrifice the quality-of-service (QoS) of applications. Prior work has demonstrated that there is significant redundancy in the content of the sensed data. By judiciously reducing the redundant data, the data size and the load can be significantly reduced, thereby reducing resource cost, facilitating the timely delivery of unique, probably critical information and enhancing QoS. This paper presents a survey of existing works for the mobile crowdsensing strategies with emphasis on reducing the resource cost and achieving high QoS. We start by introducing the motivation for this survey, and present the necessary background of crowdsensing and IoT. We then present various mobile crowdsensing strategies and discuss their strengths and limitations. Finally, we discuss the future research directions for mobile crowdsensing. The survey addresses a broad range of techniques, methods, models, systems and applications related to mobile crowdsensing and IoT. Our goal is not only to analyze and compare the strategies proposed in the prior works but also to discuss their applicability towards the IoT, and provide the guidance on the future research direction of mobile crowdsensing.**

***Index Terms*—Mobile crowdsensing; Redundancy elimination; Cost-effectiveness; Quality of service; Internet of things**

I. Introduction

In recent years, an increasing number of sensing devices and wireless networks emerge in our living environments, creating the Internet of Things (IoT) integrating the cyber and physical objects [1]–[12]. As exposed in [13], IoT will have a high impact on potential users' behavior because it integrates five layer middleware architecture (i.e., applications, service composition, service management, object abstraction and objects) and identification, sensing and communication technologies. Figure 1 shows the architecture of IoT (right) and the architecture of its five layer middleware (left). According to the *Top 10 predictions of 2014* from the Gartner, IoT will be the fast-growing, largest market potential and the most attractive emerging economy, thereby becoming the focus of attention in the field of networking [14].

Mobile crowdsensing refers to the wide variety of sensing models in which the individuals collectively share data and extract information to measure and map phenomena of common interest [15], [16]. Mobile crowdsensing is emerging as a distributed paradigm, and it lies at the intersection between the IoT and the volunteer/crowd-based scheme. Mobile crowdsensing creates a new way of perceiving the world to greatly extend the service of IoT and explore a new generation of intelligent networks, interconnecting things-things, things-people and people-people. Usually, the mobile crowdsensing applications are deployed on contributing nodes, such as mobile, personal devices that can be used to sense the physical environment and provide sensor data to mobile application server. Recently, various kinds of applications have been developed to realize the potential of mobile crowdsensing throughout daily life, such as environmental quality monitoring [17], [18], noise pollution assessment [19], [20], and traffic monitoring [21].

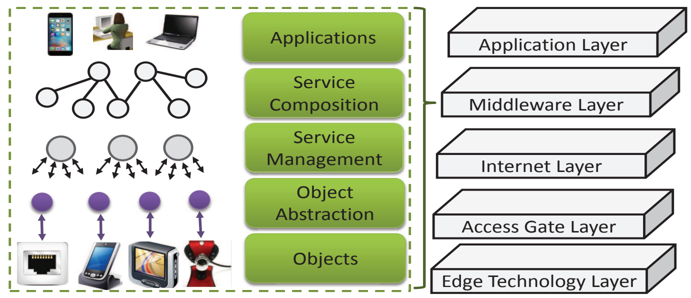

Fig. 1: Architecture of the Internet of Things (IoT) (right) and the architecture of its five layer middleware (left).

Mobile Crowdsensing requires a large number of participants (individuals) to sense the surrounding environment using the sensing devices (e.g., smartphone) with built-in sensors. It is well-known that in such a large-scale system, the sensing devices continuously generate a huge mounts of data (raw sensor data), which consumes much resource [22] (e.g., bandwidth, energy, etc.). However, the sensing devices have limited resources. Due to the limited resource, the quality of the data collected can be even sacrificed in the scenario of bandwidth constrained networks because of the heavy traffic load [23], [24]. Therefore, the resource limitation imposes a key challenge [23]–[28]. For example, images collected in the disaster area take an important role in disaster relief, the images collected may not be able to be uploaded in time due to the limited bandwidth, which can incur huge cost. Another example is that most sensing applications require location information, however GPS, as a widely used space-based navigation system, has a high power consumption. This can reduce the quality of data (location information) collected. Thus, the resource limitation always hinders the necessary participation and widescale adaption of the targeting applications [25].

Although mobile crowdsensing is a new emerging paradigm, it has been applied in real applications [29], [30]. The application of mobile crowdsensing attracts great attention from both academic and business communities, which started investigating the commercial exploitation of mobile crowdsensing [31]. However, the adoption of mobile crowdsensing approach in business context requires the guarantee of the quality-of-service (QoS). Hence, QoS is one of the most important arising issues. Therefore, QoS-driven policies are needed to deal with the application non-functional issues to guarantee QoS.

In this paper, we review the mobile crowdsensing techniques and challenges. Our focus is to discuss the resource limitation and QoS (e.g., data quality) issues and solutions in mobile crowdsensing. Apparently, a better understanding of resource management and QoS estimation in mobile crowdsensing can help us design a cost-effective crowdsensing system that can reduce the cost by fully utilizing the resource and improve the QoS for users, which manifests the significance of our survey.

Our objectives in reviewing the literature are threefold: 1) to learn what are the problems existing in mobile crowdsensing and how the proposed techniques have helped to develop solutions in the past; 2) to learn the strengths and limitations of different mobile crowdsensing techniques for smartly managing the resource to achieve low cost and good QoS, and how can we use those techniques to better solve similar problems in the future in different paradigms such as the IoT; 3) to provide guidance on the future research directions of mobile crowdsensing for IoT.

The remainder of this paper is organized as follows. Section II introduces the concepts of IoT and mobile crowdsensing. Section III describes the strategies of mobile crowdsensing. Section IV describes the challenges of mobile crowdsensing and the future research directions. Section V concludes this paper with remarks on our future work.

II. Background

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

A. Internet of Things

During the past 10 years, the IoT has drawn great attention in both academia and business communities. The potential capabilities of IoT [13] bring the interest of both academia and business communities. IoT is expected to create a world where all the objects around us are connected to the Internet, and eventually, it aims at creating 'a better world for human beings' [32].

The term 'Internet of Things' was firstly coined by Kevin Ashton [33] in 1998. Later, the International Telecommunication Union (ITU) formally introduced the concept of IoT in 2005 [34]. Currently, there is no standard definition for IoT. We use the following definition given by the work [35] as the definition for IoT because it characterizes the broader version of IoT.

- Definition by the work [35]: "The Internet of Things allows people and things to be connected Anytime, Anyplace, with Anything and Anyone, ideally using Any path/network and Any service."

IoT is a new emerging paradigm, and it is a very broad version. The research into the IoT is still on the way. The potentialities of the IoT enable the development of a large number of applications in many domains. The application domains can be primarily divided into four categories [13]: transportation and logistics domain, healthcare domain, smart environment (e.g., home, plant) domain, personal and social domain.

B. Mobile Crowdsensing

Mobile crowdsensing uses the sensing devices (e.g., smartphone), equipped with sensors, to collect data (raw sensor data) from the surrounding environment. Mobile crowdsensing usually requires a large quantity of participants to sense the environment using the sensing devices. Based on the involvement of participants in sensing actions, mobile crowdsensing can be categorized as: participatory and opportunistic [36]. Mobile crowdsensing has many applications. Based on the type of phenomenon being measured or mapped, the mobile crowdsensing applications can be divided into three categories: (a) Environmental application, (b) Infrastructure, and (c) Social application [15].

The basic mobile crowdsensing procedure includes three steps: data collection, data storage and data upload. Data collection is the first phase of the mobile crowdsensing. The strategies for data collection usually can be divided into three categories [10]:

- All the data is collected by the user manually by controlling the sensing devices, such as smartphone with specific application. This approach is attention-consuming and inefficient.
- Data collection is partially controlled by the user and by sampling, which is performed periodically. Sometimes, the data can be collected opportunistically, i.e., when the user opens some applications.
- Context-aware data sensing is triggered by predefined context, such as a particular location or time slot. This method releases the user from focusing on the crowdsensing tasks and makes it practical.

Deduplication. Deduplication is a method to eliminate redundant data in the data collection phase to reduce resource cost and improve application QoS. Data deduplication is an essential part for reducing the cost of mobile crowdsensing implementation. As in most of computation scenarios, data deduplication in mobile crowdsensing performs filtering and compressing functions on the raw data collected by the sensing device, e.g., images from the smartphone. The deduplication is conducted on the constraint that the significance of the data being kept. Deduplication of crowdsensing data maximally makes use of the limited sensor storage and reduces the bandwidth on which the data is transferred to the data center or consumer. For example, during the data deduplication process, data is divided into chunks with fixed size. And the first unique chunk is stored and used to be compared with the following ones. The duplicated chunk will be labeled and recorded using a label in the storage. Finally, only the unique data chunks and related labels are stored and uploaded. Thus the size of the uploaded data is reduced and the bandwidth consumption will be reduced.

As the size of the data to be processed increases rapidly, the methods of deduplication developed extremely fast to meet the requirement of the industry and research all over the world. From the pespective of the phase at which the deduplication occurs, the data deduplication approaches can be categorized as real-time deduplication and post-process deduplication.

Real-time deduplication refers to hashing and compressing the data when acquiring the data. Duplicated data acquired by the sensing device will be detected based on the stored data chunk. If the new data is judged as duplicated, it will not be stored in the sensing device, neither be uploaded to the data center. The advantage of this strategy is to lower the required storage of local sensing devices. However, it shifts the computation burden from the data center to the terminals. For some commodity sensing devices like smartphones, the real-time computation capacity is limited, so this strategy may not be practical. Hence, the post-process strategy can be adopted to relieve the real-time computation burden of local sensing devices. Specifically, the data acquired is stored first and then be processed for deduplication. The trade-off of this method is the relative high storage requirement and the storage overwriting risk when the storage margin is small.

III. Existing Mobile Crowdsensing Strategies

In this section, we describe different mobile crowdsensing strategies aiming to reduce the resource consumption in order to reduce the resource cost and improve QoS.

Previous works demonstrate that there is significant redundancy in the content of the data [24], [37]. In many cases, sensors are likely to collect very similar kinds of data from related sensors [37]. Thus, it is important and necessary to eliminate the redundant data, which on the one hand can reduce the resource consumption and thus reduce the cost (e.g., bandwidth cost, energy cost, etc.), and on the other hand can improve the QoS of timely information delivery by reducing the traffic load. One of the key challenges here however, is detecting 'what data is similar'. Another key challenge is how to eliminate the similar data while ensuring high QoS (e.g., without compromising the quality of the data, timely delivery of valuable data). To handle the problem caused by limited available resources, many methods have been proposed. Below, we present a review of previously proposed strategies.

A. Different Mobile Crowdsensing Strategies for Reducing Resource Cost

Aggarwal *et al.* [37] discussed real-time algorithms for reducing the volume of the data collected in sensor networks by determining the functional dependencies between sensor streams efficiently in real time, and actively collecting the data only from a minimal set of sensors. Hua *et al.* [23] presented a near-real-time and cost-effective solution under cloud assisted disaster environment. SmartEye [23] leverages two main methods, semantic hashing and space-efficient filters to aggregate the flows with similar features and provide communication services for the aggregated flow.

In bandwidth constrained network, Dao *et al.* [24] introduced a method focusing on recognizing the similar contents in images and videos, by leveraging the metadata uploaded first to distinguish the similarity of the data. According to their experimental results on a testbed and the simulation results using NS3, the rate of successful similarity detection is up to 70%. A number of researchers also dealt with the data redundancy reduction by detecting the similarity among the data, such as images or videos. For example, Weinsberg *et al.* [38] proposed a framework called CARE, which eliminates the redundancy of the image for transferring data with constrained bandwidth while maintaining the quality of the service. In comparison with the former method in [24], CARE assumes that the infrastructure is unavailable, which is reasonable when the disaster happens, and makes use of peer-to-peer strategy to eliminate redundant data. In mobile platform real-time crowdsensing, Wanita *et al.* [39] designed a system for collecting data via instantaneously data analysis and process. To reduce bandwidth consumption and save the energy for mobile devices, their CAROMM is able to acquire various stream data by mobile devices and process them based on context attached, e.g., the location and time mark on photos, finally contributing to the relevant data retrieval from the dataset.

Riteau *et al.* [40] adopted a data deduplication strategy to reduce the storage and bandwidth consumption for the applications which require a great deal of data to be kept and conveyed. Based on WANs, a distributed data deduplication method and a message-delivery model were provided. However, the semantics of the content was not considered to further improve the performance of the approach.

To address the high energy consumption problems involved in smartphone based crowdsensing applications, Nicholas *et al.* [10] proposed an energy effective crowdsensing strategy by taking advantage of opportunistic application run by the users. The solution is called Piggyback CrowdSensing (PCS), and it depends on a predictive model to find the optimal time slot to perform the sensing task. Prediction is an effective way to avoid meaningless cost and lower the overhead, e.g., taking into account location information. The data (i.e., images) from exactly the same location tend to contain the same information. Besides, their analysis on the application specifics can also contribute to the overall cost-reduction. Gorlatova *et al.* [27] presented solutions on estimating harvested energy from acceleration records. In order to characterize the energy availability related to particular human behaviors, the work [27] analyzes a motion dataset with over 40 participants, and an energy allocation algorithm with accessible IoT node solution designing has been developed and evaluated based on the collected measurements.

B. Different Crowdsensing Strategies for Achieving Good QoS

Below, we introduce a list of methods for achieving good QoS in mobile crowdsensing.

Xu *et al.* [41] proposed Compressive CrowdSensing (CC-S) which is a framework for applying compressive sensing techniques to mobile crowdsourcing scenarios. CCS enables compressive sensing techniques to be applied to mobile crowdsensing by providing significantly reduced amounts of manually collected data and maintaining acceptable levels of overall accuracy at the same time.

Yan *et al.* [42] proposed CrowdSearch for searching images using mobile phones. CrowdSearch integrates the strategy of automated image search into the real-time validation of human. They combined local processing on mobile phones and backend processing on remote servers to implement the process of image search. By balancing accuracy and monetary cost, CrowdSearch finds a trade-off between accuracy and monetary cost and ensures user-specified deadlines for responses to search queries simultaneously. To improve the quality of images, CrowdSearch presents a new prediction algorithm to determine the results needed to be validated, and determine when and how to validate these results.

Due to the limited resource, it is a challenge to transfer a huge amount of crowdsensed data. To address this challenge, Wang *et al.* [43] proposed a framework called SmartPhoto, to quantify the quality (utility) of crowdsensed photos based on the accessible geographical and geometrical information (referred to as metadata), which contains the information of the smartphone's orientation, location and all related parameters of the built-in camera. With the metadata, it can be inferred where and how the photo is taken. Also, SmartPhoto only transmits the most useful photos. They also studied three optimization problems on the trade-offs between photo utility and resource constraints. Moreover, they designed efficient algorithms with theoretical proofs of the performance of the algorithms. Finally, by using Android based smartphones, they implemented SmartPhoto in a testbed with techniques designed to improve the accuracy of the collected metadata by reducing sensor reading errors.

Xu *et al.* [25] studied compressive sensing under the scenarios in which different samples have different costs. This work tries to balance the minimization of the total sample cost and the recovery accuracy, and designs Cost-aware Compressive Sensing (CACS) for incorporating the samples' diversity on cost into the compressive sensing framework. The CACS has been applied to networked sensing systems.

To maximize the aggregate data utility, Li *et al.* [44] studied how to the aggregate data utility under the constraint on budget in mobile crowdsensing. They presented a combinatorial auction mechanism that utilizes a redundancy-aware reverse auction framework. The auction mechanism is mainly composed of two parts: an approximation algorithm used for winning bids determination and a critical payment scheme.

IV. Challenges and Future Research Directions

In this section, we first discuss further challenges related to crowdsensing for IoT, and then we provide guidance on the future research trends of crowdsensing for IoT.

A. Challenges in Mobile Crowdsensing

1) Automated configuration of sensors: In traditional pervasive/ubiquitous computing, only a limited number of sensing devices (e.g., sensors) are connected to the applications (e.g., smart farm, smart river). However, in IoT, a large number of sensing devices are expected to be connected together over the Internet. Therefore, the connection and configuration of sensing devices to applications become a key challenge. It is infeasible to connect all sensing devices manually to an application or to a middleware [45]. An automated or at least semi-automated process should be available to connect sensing devices to applications. To accomplish the tasks of connecting sensing devices to applications, applications should be capable of understanding the sensing devices (e.g., capabilities). Several recent developments such as Transducer Electronic Data Sheet (TEDS) [46], Open Geospatial Consortium (OGC) Sensor Web Enablement related standards like Sensor Markup Languages (SensorML) show the future trends of carrying out research work for addressing the challenge of connection and configuration of sensors to applications.

2) Resource limitations: Sensing devices (e.g., sensors and mobile phones) usually have limited resources, and the resource limitations arise as a challenge for crowdsensing. Although more resources (e.g., computing, bandwidth) are provided for mobile phones compared to mote-class sensors, mobile phones still face the problem of resource limitations [47], [48].

Different types of sensed data may be independent with each other because of the multi-modality sensing capabilities of sensing devices. In practical scenarios, different types of sensed data may be used for the same purpose. However, the diversities on the quality and resource consumption of the sensed data pose an obstacle for improving the quality of data with low resource consumption. Therefore, it is still a challenge to improve the quality of data and minimize the resource consumption.

3) Privacy, security, and data integrity: The sensing devices potentially collect sensitive data of individuals [11], [39], [49]–[55], thus privacy arises as a key problem. For example, the GPS sensor readings usually record the private information of individuals (e.g., the routes they take during their daily commutes, and locations [56]). By sharing the GPS sensor measurements, individuals' privacy can be revealed. Hence, it is important and necessary to preserve the security and privacy of an individual. Also, the GPS records the information which is from daily commutes shared within a larger community and can be used to learn the information of traffic congestion in a city [57]. Thus, it is also necessary to enable the crowdsensing applications so that individuals can better understand their surroundings and can ultimately benefit from the information sharing. To well preserve the enormous amounts of private information of individuals, not only methodology efforts but also systematic studies are needed. The AnonySense architecture, proposed in [58], can support the development of privacy-aware applications based on crowdsensing. Also, it is important to guarantee that an individual's data is not revealed to untrustworthy third parties. For example, malicious individuals usually contribute erroneous sensor data. Meanwhile, for their own benefit, malicious individuals may intentionally pollute the sensing data. The lack of control mechanisms to guarantee source validity and data accuracy can result in information credibility issues. Therefore, it is necessary to develop trust preservation and abnormal detection technologies to ensure the quality of the obtained data.

The problem of data integrity that ensures the integrity of individuals' sensor data, also needs to be well addressed. In the existing literature [59], [60], although some methods have been proposed, they typically rely on co-located infrastructure that may not be installed as a witness and have limited scalability, which makes such kind of methods prohibitive and unavailable at times. The reason behind this is that the approach relies on the inputs which is from the installation of expensive infrastructure. Another approach for handling data integrity problem is to sign the sensor data (e.g., typically, trusted hardware installed on mobile phones are used for this purpose), i.e., a trusted platform module signs a SHA-1 digest of the sensor data. This approach is potentially problematic due to the reason that the verification process has to be done even in the software.

B. Future Research Directions

Below we present some future research directions of crowdsensing for IoT.

1) Optimization of multiple factors like localization, prediction, energy budget: The trade-off between higher location accuracy and lower energy consumption for the mobile crowdsensing devices is critical to successfully implement various algorithms [7], [8], [61]–[63]. For example, in the solution proposed by Lane *et al.* [10], to lower the energy overhead based on the context information, such as position, its real-world performance suffers from the inaccurate localization model. Besides, for mobile crowdsensing, especially smartphone based platform, more than one sensor can be used to collect the data and sense the context, such as dynamic status, localization, and noise magnitude. Thus, the reliability and the amount of information of context may be increased as in the work [39] in which the proposed CAROMM is able to acquire various stream data from mobile devices and process them based on context attached, e.g., the location and time mark on photos. This further contributes to the performance of crowdsensing.

2) Privacy protection: Privacy protection is a principal issue that has not yet been well addressed, especially in the crowdsensing area. There is a large body of work focusing on privacy protection [10], [39], [49]. The CAROMM framework, making use of the context of the data from user's smartphone, bears high risks to leak the privacy information of users since the information like location and time, which are required to be protected. Obviously, the privacy risk must be reduced to an acceptable level before any crowdsensing activity is conducted. Otherwise, the user's privacy may be exposed to the public. Lane *et al.* [10] conducted research on the automatic data anonymization by masking particular information from the raw data sensed by the local smartphone.

3) Social Internet of Things: Real humans are believed to understand and answer better than a machine, and they are the most "intelligent machines" [64], [65]. A large number of individuals tied in a social network can provide better answers to complicated problems than a single individual (or even a knowledgeable individual) [66]. The collective intelligence emerging in social networks can help users find information (e.g., answers to their problems), which attracts many interests. Social networks have the advantage of efficiently discovering and distributing services, and social networks are utilized by many systems, such as Yahoo! Answers, Facebook, for sharing the information (e.g., knowledge). There is a great potential and prospect for integrating social networking into Internet of Things, which will be an important research direction.

V. Conclusions

The IoT has attracted much attention over the past few years. Numerous sensing devices emerge in our living environments, which creates the IoT integrating the cyber and physical objects. Mobile crowdsensing plays an important role in the IoT paradigm. Sensors continuously generate enormous amounts of data, which consumes much resource, such as storage resource for storing data and bandwidth resource for data transfer. Previous works demonstrate that there is significant amount of redundancy in sensor data. Thus, redundancy elimination of sensor data is important and worthwhile, which can significantly reduce the cost (e.g., bandwidth cost for data transfer) and facilitate the timely delivery of critical information by reducing the traffic load, and thereby help achieving good QoS. In this paper, we review the mobile crowdsensing techniques and challenges. We focus on the discussion of the resource limitation and QoS (e.g., data quality) issues and solutions in mobile crowdsensing. A better understanding of resource management and QoS estimation in mobile crowdsensing can help us design a cost-effective crowdsensing system that can reduce the cost by fully utilizing the resource and improve the QoS for users. In the end of the paper, we discuss some of the trends in the mobile crowdsensing. In the future, we will give an in-depth study of challenges and techniques, solutions for addressing challenges in mobile crowdsensing for IoT, and we will also analyze the production systems and provide case studies.

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References

[1] D. Zordan, B. Martinez, I. Vilajosana, and M. Rossi. On the performance of lossy compression schemes for energy constrained sensor networking. *ACM Transactions on Sensor Networks*, 11(1):1–34, 2014.

[2] H. Shen, J. Liu, K. Chen, J. Liu, and S. Moyer. Scps: A social-aware distributed cyber-physical human-centric search engine. *IEEE Transactions on Computers (TC)*, 64:518–532, 2015.

[3] Y. Zhu and D. Shasha. Statstream: Statistical monitoring of thousands of data streams in real time. In *Proc. of VLDB*, pages 358–369, 2002.

[4] W. Zhang, J. Wang, and W. Feng. Combining latent factor model with location features for event-based group recommendation. In *KDD*, 2013.

[5] K. Tangwongsan, H. Pucha, D. G. Andersen, and M. Kaminsky. Efficient similarity estimation for systems exploiting data redundancy. In *Proc. of INFOCOM*, 2010.

[6] W. Willett, S. Ginosar, A. Steinitz, B. Hartmann, and M. Agrawala. Identifying redundancy and exposing provenance in crowdsourced data analysis. *IEEE Trans. Vis. Comput. Graphics*, 19(12):2198–2206, 2013.

[7] S. Hasan and E. Curry. Approximate semantic matching of events for the internet of things. *ACM TOIT*, 14(1):Article 2, 2014.

[8] H. Kirak, L. David, R. Umakishore, O. Beate, and K. Boris. Opportunistic spatio-temporal event processing for mobile situation awareness. In *Proc. of ACM DEBS*, pages 195–206, Arlington, June 2013.

[9] A. Kumbhare, Y. Simmhan, and V. K. Prasanna. Exploiting application dynamism and cloud elasticity for continuous dataflows. In *SC*, 2013.

[10] N. D. Lane, Y. Chon, L. Zhou, Y. Zhang, F. Li, D. Kim, G. Ding, F. Zhao, and H. Cha. Piggyback crowdsensing (pcs): Energy efficient crowdsourcing of mobile sensor data by exploiting smartphone app opportunities. In *Proc. of SenSys*, Rome, November 2013.

[11] J. Li, X. Chen, M. Li, P. P. C. Lee, and W. Lou. Secure deduplication with efficient and reliable convergent key management. *TPDS*, 25(6):1615–1625, 2014.

[12] Y. Lin and H. Shen. Vshare: A wireless social network aided vehicle sharing system using hierarchical cloud architecture. In *IoTDI*, 2016.

[13] L. Atzori, A. Iera, and G. Morabito. The internet of things: A survey. *Computer Networks*, 54(15):2787–2850, October 2010.

[14] Gartner. http://www.gartner.com [accessed in Mar. 2016].

[15] R.K. Ganti, F. Ye, and H. Lei. Mobile crowdsensing: Current state and future challenges. *IEEE Comm. Mag.*, 49(11):32–39, November 2011.

[16] D. Peng, F. Wu, and G. Chen. Pay as how well you do: A quality based incentive mechanism for crowdsensing. In *Proc. of MOBIHOC*, 2015.

[17] Creek watch. http://creekwatch.researchlabs.ibm.com/, 2010 [accessed in Mar. 2016].

[18] Opensense. http://www.opensense.ethz.ch/trac/, 2010 [accessed in Mar. 2016].

[19] N. Maisonneuve, M. Stevens, M. Niessen, and L. Steels. Noisetube: Measuring and mapping noise pollution with mobile phone. In *Information Technologies in Environmental Engineering*, 2009.

[20] R. Rana, C. Chou, S. Kanhere, N. Bulusu, and W. Hu. Ear-phone: An end-to-end participatory urban noise mapping system. In *ISPN*, 2010.

[21] D. Zhang, H. Xiong, L. Wang, and G. Chen. Crowdrecruiter: Selecting participants for piggyback crowdsensing under probabilistic coverage constraint. In *ACM UbiComp*, pages 703–714, Seattle, 2014.

[22] J. Liu, L. Yu, H. Shen, Y. He, and J. Hallstrom. Characterizing data deliverability of greedy routing in wireless sensor networks. In *Proc. of SECON*, Seattle, June 2015.

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

[24] T. Dao, A. K. Roy-Chowdhury, H. V. Madhyastha, S. V. Krishnamurthy, and T. L. Porta. Managing redundant content in bandwidth constrained wireless networks. In *Proc. of CoNEXT*, pages 349–361, 2014.

[25] L. Xu, X. Hao, N. D. Lane, X. Liu, and T. Moscibroda. Cost-aware compressive sensing for networked sensing systems. In *IPSN*, 2015.

[26] Y. Xu, P. Tang, and J. Liu. Resource Scheduling Algorithm based on Multi-target Balance in Enterprise Gloud Storage System. *Journal of Theoretical and Applied Information Technology*, 48(3):1578–1583, 2013.

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

[28] H. Shen and Z. Li. New bandwidth sharing and pricing policies to achieve a win-win situation for cloud provider and tenants. In *Proc. of INFOCOM*, 2014.

[29] Y. Chon, N. D. Lane, F. Li, H. Cha, and F. Zhao. Automatically characterizing places with opportunistic crowdsensing using smartphones. In *Proc. of ACM UbiComp*, pages 481–490, New York, NY, USA, 2012.

[30] P. Mohan, V. Padmanabhan, and R. Ramjee. Nericell: rich monitoring of road and traffic conditions using mobile smartphones. In *SenSys*, 2008.

[31] M.-R. Ra, B. Liu, T. L. Porta, and R. Govindan. Medusa: A programming framework for crowd-sensing applications. In *MobiSys*, 2012.

[32] A. Dohr, R. Modre-Opsrian, M. Drobics, D. Hayn, and G. Schreier. The internet of things for ambient assisted living. In *ITNG*, 2010.

[33] K. Ashton. That 'internet of things' thing in the real world, things matter more than ideas. *RFID Journal*, June 2009.

[34] International Telecommunication Union. Itu internet reports 2005: The internet of things. International Telecommunication Union, Workshop Report, November 2005.

[35] P. Guillemin and P. Friess. Internet of things strategic research roadmap. The Cluster of European Research Projects, Tech. Rep., Sept. 2009.

[36] S. Jami, A. Basalamah, A. Lbath, and M. Youssef. Hybrid participatory sensing for analyzing group dynamics in the largest annual religious gathering. In *Proc. of ACM UbiComp*, pages 547–558, Osaka, 2015.

[37] C. C. Aggarwal, Y. Xie, and P. S. Yu. On dynamic data-driven selection of sensor streams. In *Proc. of KDD*, pages 1226–1234, 2011.

[38] U. Weinsberg, Q. Li, N. Taft, A. Balachandran, V. Sekar, G. Iannaccone, and S. Seshan. Care: Content aware redundancy elimination for challenged networks. In *Proc. of Hotnets*, Seattle, October 2012.

[39] W. Sherchan, P. P. Jayaraman, S. Krishnaswamy, A. Zaslavsky, S. Loke, and A. Sinha. Using on-the-move mining for mobile crowdsensing. In *Proc. of MDM*, pages 115–124, 2012.

[40] J. Roemer, M. Groman, Z. Yang, Y. Wang, C. C. Tan, and N. Mi. Improving virtual machine migration via deduplication. In *MASS*, 2014.

[41] L. Xu, X. Hao, N. D. Lane, X. Liu, and T. Moscibroda. More with less: Lowering user burden in mobile crowdsourcing through compressive sensing. In *Proc. of ACM UbiComp*, pages 659–670, Osaka, 2015.

[42] T. Yan, V. Kumar, and D. Ganesan. Crowdsearch: Exploiting crowds for accurate real-time image search on mobile phones. In *MobiSys*, 2010.

[43] Y. Wang, W. Hu, Y. Wu, and G. Cao. Smartphoto: A resource-aware crowdsourcing approach for image sensing with smartphones. In *Proc. of MOBIHOC*, pages 113–122, Philadelphia, August 2014.

[44] J. Li, Y. Zhu, J. Yu, Q. Zhang, and L. Ni. Towards redundancy-aware data utility maximization in crowdsourced sensing with smartphones. In *Proc. of ICDCS*, 2015.

[45] C. Perera, P. Jayaraman, A. Zaslavsky, P. Christen, and D. Georgakopoulos. Dynamic configuration of sensors using mobile sensor hub in internet of things paradigm. In *Proc. of ISSNIP*, Melbourne, 2013.

[46] IEEE standard for a smart transducer interface for sensors and actuators wireless communication protocols and transducer electronic data sheet (TDES) formats, 2007.

[47] E. Miluzzo, N. D. Lane, K. Fodor, R. Peterson, H. Lu, M. Musolesi, S. B. Eisenman, X. Zheng, and A. T. Campbell. Sensing meets mobile social networks: The design, implementation and evaluation of the cenceme application. In *Proc. of SenSys*, Raleigh, November 2008.

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

[49] I. Krontiris and T. Dimitriou. Privacy-respecting discovery of data providers in crowd-sensing applications. In *Proc. of DCoSS*, 2013.

[50] J. Ballesteros, B. Carbunar, M. Rahman, N. Rishe, and S. Iyengar. Towards safe cities: A mobile and social networking approach. *TPDS*, PP(99):1, 2013.

[51] A. Zanella, N. Bui, A. Castellani, L. Vangelista, and M. Zorzi. Internet of things for smart cities. *IEEE Internet Things J.*, 1(1):22–32, 2014.

[52] Y. Chen, J. Zhou, and M. Guo. A context-aware search system for internet of things based on hierarchical context model. *Telecommunication Systems*, 2015.

[53] S. A. Stansfeld. Noise pollution: non-auditory effects on health. *British Medical Bulletin*, 68(1):243–257, 2003.

[54] P. Rothenpieler, B. Altakrouri, O. Kleine, and L. Ruge. Distributed crowd-sensing infrastructure for personalized dynamic iot spaces. In *Proc. of URB-IOT*, Rome, October 2014.

[55] F. A. Teixeira, G. V. Machado, F. M. Q. Pereira, and L. B. Oliveira. Siot: Securing the internet of things through distributed system analysis. In *Proc. of IPSN*, pages 310–321, 2015.

[56] J. Krumm. A survey of computational location privacy. *Personal and Ubiquitous Computing*, 13(6):391–399, 2009.

[57] B. Hull, V. Bychkovsky, Y. Zhang, K. Chen, M. Goraczko, A. Miu, E. Shih, H. Balakrishnan, and S. Madden. Cartel: A distributed mobile sensor computing system. In *Proc. of ACM SenSys*, Boulder, 2006.

[58] C. Cornelius, A. Kapadia, D. Kotz, D. Peebles, M. Shin, and N. Triandopoulos. Anonysense: Privacy-aware people-centric sensing. In *Proc. of ACM MobiSys*, pages 211–224, New York, NY, 2008.

[59] V. Lenders, E. Koukoumidis, P. Zhang, and M. Martonosi. Location-based trust for mobile user-generated content: Applications, challenges, and implementations. In *Proc. of HotMobile*, pages 60–64, 2008.

[60] S. Saroiu and A. Wolman. Enabling new mobile applications with location proofs. In *Proc. of HotMobile*, pages 1–6, 2009.

[61] J. Howe. The rise of crowdsourcing. *Wired Magazine*, 14(06):1–5, 2006.

[62] H. Susmita and S. Anjali. Identity management framework for cloud based internet of things. In *Proc. of SecurIT*, Kollam, August 2012.

[63] I. Vasilescu, K. Kotay, D. Rus, M. Dunbabin, and P. Corke. Data collection, storage, and retrieval with an underwater sensor network. In *Proc. of SenSys*, 2005.

[64] H. Shen, Z. Li, J. Liu, and J. E. Grant. Knowledge sharing in the online social network of yahoo! answers and its implications. *IEEE Transactions on Computers (TC)*, 64(6):1715C1728, June 2015.

[65] J. Liu, H. Shen, and L. Yu. Question quality analysis and prediction in community question answering services with coupled mutual reinforcement. *IEEE Trans. on Services Computing (TSC)*, PP(99):1–14, 2015.

[66] L. Atzori, A. Iera, G. Morabito, and M. Nitti. The social internet of things (siot) – when social networks meet the internet of things: Concept, architecture and network characterization. *Comput. Netw.*, 56:3594–3608, 2012.