Robust Mobile Crowd Sensing: When Deep Learning Meets Edge Computing

Zhenyu Zhou, Haijun Liao, Bo Gu, Kazi Mohammed Saidul Huq, Shahid Mumtaz, and Jonathan Rodriguez

Abstract

The emergence of MCS technologies provides a cost-efficient solution to accommodate large-scale sensing tasks. However, despite the potential benefits of MCS, there are several critical issues that remain to be solved, such as lack of incentive-compatible mechanisms for recruiting participants, lack of data validation, and high traffic load and latency. This motivates us to develop robust mobile crowd sensing (RMCS), a framework that integrates deep learning based data validation and edge computing based local processing. First, we present a comprehensive state-of-the-art literature review. Then, the conceptual design architecture of RMCS and practical implementations are described in detail. Next, a case study of smart transportation is provided to demonstrate the feasibility of the proposed RMCS framework. Finally, we identify several open issues and conclude the article.

Introduction

Building a safer, more sustainable society relies on efficient monitoring of our surrounding environmental context, such as road traffic, air conditions, natural disasters, and so on. Conventional sensing techniques require the deployment of a large number of static sensor nodes, which results in significant capital expenditure (CAPEX) and operational expenditure (OPEX) [1]. Recently, we have been witnessing the rapid proliferation of smartphones, tablets and wearable devices. These mobile devices are usually equipped with a great variety of powerful sensors, such as proximity sensor, light sensor, accelerometer, barometer, and so on. Sensors that can measure environmental conditions and health status are also under development and will possibly be incorporated in the near future. By leveraging the sensing capabilities of these mobile devices, as well as the inherent mobility of their owners, it is possible to collect sensory data at a sufficient temporal-spatial granularity without deploying additional sensor nodes [2]. This new sensing paradigm is known as mobile crowd sensing (MCS). Compared to the conventional application-specific sensing architecture, it provides a cost-efficient solution, especially for large-scale sensing tasks.

This paradigm shift also gives rise to various advanced applications, for example, Sensorly [3] for monitoring speed and coverage of WiFi, LTE and 3G services, Nericell [4] for monitoring urban road and traffic conditions, and so on. However, despite the above-mentioned huge potential benefits, research and development in the field of MCS are still in its infancy. The major challenges are summarized as follows.

Lack of Incentive-Compatible Mechanisms for Recruiting Participants: The successful implementation of MCS applications requires voluntary contributions from a large number of mobile device owners. Due to the increased data usage and battery consumption incurred by data sensing, processing, and uploading, most device owners are reluctant to participate in sensing activities unless they are well compensated [5]. Especially in the scenario of information asymmetry, the private information of each device owner, for example, the cost of performing a sensing task, is generally unknown. Therefore, an effective incentive-compatible mechanism is of significant importance to elicit the private information of device owners, and motivate them to offer their communication, computing, and storage resources for performing sensing tasks.

Lack of Effective Approaches to Validate the Quality of Sensory Data: Once financial incentives are involved, self-interested device owners may deliberately provide misleading and deceptive sensory data if a higher benefit can be obtained. Since the quality of sensory data is directly related to the successful realization of sensing tasks, legendary MCS schemes without data validation will result in poor system performance and an excessive waste of money. Thus, the verification of the authenticity and relevance of the sensory data becomes an indispensable step to guarantee the reliable and cost-efficient operation of the MCS system.

High Traffic Load And Latency: Conventional MCS systems rely on a centralized server to process all the sensory data gathered from large-scale distributed sensing participants. If the centralized server is located far from the sensing field, the capacity-constrained backhaul and backbone networks may result in unpredictable latency. Hence, for delay-sensitive MCS tasks and applications, how to reduce the amount of traffic and the transmission latency is a critical challenge for reliable provisioning of quality of service (QoS) and quality of experience (QoE).

Accordingly, the above-mentioned challenges motivate us to design a robust mobile crowd sensing (RMCS) architecture to ensure reliable service provisioning and cost-efficient operation of MCS

Zhenyu Zhou and Haijun Liao are with State Key Laboratory of Alternate Electrical Power System with Renewable Energy Sources, North China Electric Power University; Bo Gu (correspondIng author) is with Kogakuin University; Kazi Mohammed Saidul Huq, Shahid Mumtaz and Jonathan Rodriquez are with Instituto de Telecomunicações, Portugal; Jonathan Rodriguez is also with the University of South Wales.

Digital Object Identifier: 10.1109/MNET.2018.1700442

systems. The proposed RMCS architecture leverages two up-to-date technologies, i.e., deep learning and edge computing, to provide robust data validation and local data processing. On the one hand, deep learning, which simulates the mechanism of the human brain for data analysis and interpretation, can enable automatic detection of forged and irrelevant data to guarantee system robustness [6]. On the other hand, edge computing, which extends the computing paradigm from centralized infrastructures to distributed network edges, can dramatically eliminate dispensable network hops and reduce transmission latency [7]. Furthermore, an incentive-compatible active participant recruitment scheme is proposed under the information asymmetry scenario.

This article is organized as follows. First, we present a thorough literature review on recent progress. Then, we introduce the proposed RMCS architecture, and present the implementation procedures. Next, we provide a case study on smart transportation to demonstrate the remarkable performance improvements in efficiency and robustness. Finally, we conclude the article, and identify several open issues.

Related Works

In this section, we present an exhaustive commentary on the development of MCS with data quality validation, deep learning assisted MCS, and edge computing enabled MCS.

The successful implementation of MCS applications lies in sensing accuracy. In [2], Xiao *et al*. proposed a secure Stackelberg game based pricing scheme for MEC to suppress fake sensing attacks, in which the sensing quality of each device owner is estimated by blind image quality assessment and majority voting. In [8], Gisdakis *et al.* presented a holistic MCS architecture to preserve user privacy and facilitate trustworthy MCS application deployment. A data quality based incentive mechanism was proposed for MCS in [5], in which MCS participants are rewarded based on their real contributions, that is, the quality of sensory data.

However, in most of the current works, the analytical-form expression of uncertain parameters such as sensing error, fake sensing attacks, and so on, is assumed as perfectly known. However, this assumption is too strong considering the complicated application scenarios and numerous practical constrains. An alternate solution is to explore deep learning for activity forecasting and feature inference, which does not require the explicit analytical model of the error data. There exist some works that have already applied deep learning on MCS to predict sensing patterns or estimate user behavior. In [9], Lane *et al*. developed a deep neural network (DNN) based inference framework for MCS, which can reliably infer context and heterogeneous user behavior from noisy data. A deep learning based recurrent neural network architecture named DeepSense was proposed in [10] to estimate and classify signals of different sensory patterns by integrating local interactions with global interactions and exploring temporal relationship.

In the above mentioned works, the implementation of deep learning for MCS is usually located at remote cloud servers. The long transmission distance and the large-volume redundant sensory data pose new challenges on timely data processing and service delivery. Edge computing provides a promising solution by executing computing tasks in the proximity of users. In [11], a privacy-preserving vehicular crowd sensing protocol was proposed to enhance security for road surface condition monitoring based on fog computing. In [7], Chen *et al*. developed an edge computing based MCS framework, which enables dynamic collaboration and resource sharing among users via device-to-device (D2D) communications. In [12], the remote cloud and edge servers are combined in a complementary manner to provide seamless task processing based on dynamic conditions of task, network, location, and resources.

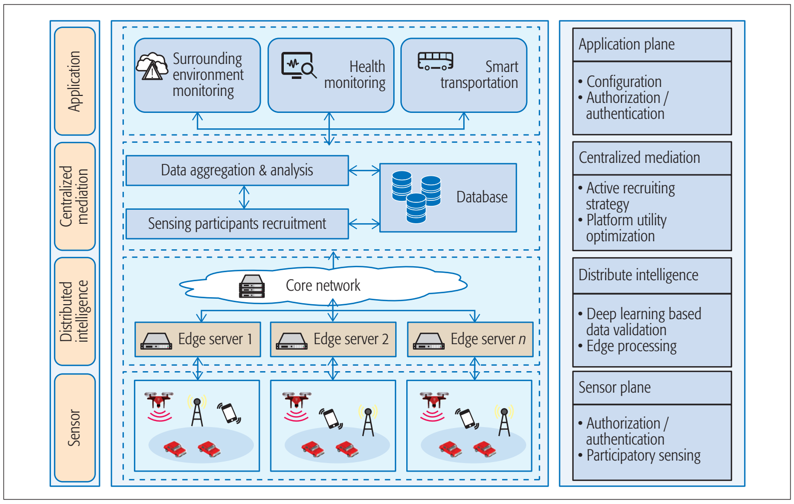

FIGURE 1. The RMCS architectrue.

Different from the previous works, we investigate the feasibility of deploying deep learning based data quality validation at network edges to improve sensing reliability and reduce transmission as well as processing latency. Furthermore, an incentive-compatible active participant recruitment scheme is proposed under the information asymmetry scenario. Then, a deep learning based data authenticity and relevance validation approach is proposed to enable automatic detection of forged and irrelevant data. The proposed scheme can effectively reduce unnecessary rewards and inefficient sensory data, and achieve the maximization of both sensing coverage and profit.

Robust Mobile Crowd Sensing Architecture and Implementation

Figure 1 shows the proposed RMCS architecture, which consists of four different planes: the sensor plane, the distributed intelligence plane, the centralized mediation plane, and the application plane. The sensor plane is composed of mobile sensing devices and network elements involved in collecting sensory data from mobile sensing devices to edge computing servers. The distributed intelligence plane offers computing, storage and communication resources between sensing devices and the centralized mediation plane. Deep learning based data validation and edge processing features are implemented in this plane. The centralized mediation plane consists of:

Due to the uncertainty of the amount of rewards that can be received, device owners are reluctant to participate in performing sensing tasks. To provide a solution, we propose a pre-contract based active participant recruiting mechanism, in which the sensing location, sensing schedule, and the amount of monetary reward between the sensing platform and potential participants are determined in advance.

- Traditional cloud computing data centers for aggregating sensory data from the distributed intelligence plane.
- A sensing participant recruiting module that dispatches sensing tasks to the distributed intelligence plane.
- Database servers that maintain historical sensory data.

The application plane includes a series of MCS applications such as surrounding environment monitoring, health monitoring, smart transportation, and so on. With the standard application programming interfaces (APIs) between the centralized control and application planes, applications can publish their sensing tasks by specifying the phenomena of interest, targeted locations and the total budget for rewarding participants, and so on.

The implementation of the RMCS framework is summarized as follows.

Active Participant Recruitment

Participant recruitment is crucial for the RMCS framework to improve service coverage area and effectiveness. The implementation of participant recruitment involves multiple stakeholders: data requesters who wish to collect sensory data from mobile devices; device owners who provide sensory data; and a sensing platform that acts as a third-party authority to recruit participants to perform sensing tasks. Due to the uncertainty of the amount of rewards that can be received, device owners are reluctant to participate in performing sensing tasks. To provide a solution, we propose a pre-contract based active participant recruiting mechanism, in which the sensing location, sensing schedule, and the amount of monetary reward between the sensing platform and potential participants are determined in advance.

Since the private information of each device owner is generally not a priori under the scenario of information asymmetry, the active participant recruiting mechanism should be incentive compatible, that is, the private information of device owners can be effectively elicited. Specifically, we employ the reverse Vickrey-Clarke-Groves auction with a reservation price (RVRP) for monetary reward determination. The RVRP auction is a type of multi-item sealed-bid auction, that is, device owners submit bids that indicate their sensing costs without knowing the bids of the others in the auction. Particularly, it is always optimal for a device owner to bid their sensing cost truthfully regardless of the other bids. Furthermore, to recruit participants in locations with low population density, for example, rural areas, the proposed mechanism motivates the participation of not only device owners located inside or in the vicinity of the targeted locations, but also device owners who can arrive at targeted locations within a specified period of time. For instance, passengers on a train that are going to pass through a targeted location at a specified time can be considered as potential participants. If they are well compensated, device owners may even move a distance to participate in sensing activities.

Active participant recruitment can be implemented as follows.

Step 1: Data requesters publish their task descriptions on the sensing platform by specifying the phenomena of interest, targeted locations and the total budget for rewarding participants.

Step 2: After receiving the task description, the sensing platform begins to recruit participants by sending notifications to potential participants.

Step 3: Each device owner claims for an interested location and bids on the sensing cost, that is, the minimum amount of money they are willing to accept to perform the sensing task.

Step 4: The platform decides the winners and the corresponding rewards, which will be illustrated in detail later. The platform then signs a pre-contract with the winners indicating the sensing location, schedule and the amount of reward.

Step 5: The winners perform the sensing task and upload the sensed data back to the platform.

Step 6: The platform aggregates all sensed data and reports to the task requester.

In the RVRP auction, all bids are sorted in ascending order based on the value of the bid, and the device owners with the same bid value are further sorted in an ascending order according to their distance to the targeted location. The rationale behind this is that the longer the distance, the higher the probability that the participant will fail to reach the targeted location. We use n_l to denote the number of winners that are going to provide sensory data, and k_l to denote the number of bids that are lower than the reservation price R at location l. Reservation price is a design parameter that represents the maximum amount of reward for each participation. Hence, $n_l \le k_l$ for any targeted location.

If $n_l < k_l$, the n_l lowest bidders are the winners and the reward that each winner receives for providing sensory data is equal to the $(n_l + 1)$-th highest bid. On the other hand, if $n_l = k_l$, then all the bidders are winners and receive the same reward R. The reward for providing sensory data at location l is denoted by $p_l(n_l)$ as follows:

$$p_l(n_l) = \begin{cases} b_{n_l+1} & \text{if } n_l < k_l \\ R & \text{if } n_l = k_l \end{cases}. \tag{1}$$

We assume that each device owner i has its own sensing cost v_i, which is private information. The payoff u_i depends on the bidding strategy b_i and those of the other device owners. Since the RVRP auction is incentive compatible, the optimal bidding strategy for device owner i is to bid their sensing cost truthfully, that is, $b_i = v_i$. We denote the platform utility as a logarithmic function (strict increasing and concave) of independent measurements at each location l. The platform utility optimization problem under the budget constraint is formulated as follows:

$$\begin{aligned} &\max_{\{n_l\}} \sum_{l \in \mathcal{L}} w \log(n_l + 1) \\ &\text{s.t.} \quad \sum_{l \in \mathcal{L}} p_l(n_l) \times n_l \le C \\ &\qquad n_l \le k_l, \forall l \in \mathcal{L}, \end{aligned} \tag{2}$$

where w is a factor indicating the scale of the utility function, and C is the total budget of the data requester.}

Deep Learning Based Data Validation

After the active participant recruitment procedure, selected participants should collect and upload sensory data to fulfill the requirements specified in the pre-contract. However, self-interested device owners may cheat and provide false sensory data to get higher benefits. Two common cheating approaches are to provide computer-generated forged data, and to provide irrelevant data inadvertently or maliciously. The forged and irrelevant data not only degrades the overall sensing accuracy, but also results in unnecessary rewards. Therefore, deep learning based data validation is essential to guarantee system robustness and efficiency.

Figure 2 shows a straightforward representation of the proposed deep learning based data validation scheme. There are three major steps: preliminary filtering, data authentication verification, and data relevance identification. Taking image data as an example, in the preliminary filtering step, edge detection is utilized to measure the sharpness of an optical image. Specifically, the gradient data of the edge brightness variation can be calculated by performing edge extraction on the tracked target area. Then, depending on the specific application scenarios, different thresholds can be specified to filter out unqualified images, for example, images with unsatisfactory clarity, out of focus, and so on.

To realize data authentication verification and data relevance identification, a convolutional neural network (CNN) with the ability of pattern classification and recognition is adopted, which is composed of an input layer, multi-hidden layers and an output layer [6]. The input variables include the temporal sequence of data, that is, sensory data from the same location at different time, and the spatial sequence of data, that is, sensory data that are collected simultaneously from adjacent sensing nodes. Based on these inputs, the CNN network is supposed to filter out forged and irrelevant data with a high accuracy. Furthermore, localized connections are generated whereby each region of the input is connected to a neuron in the output as shown in Fig. 2.

A substantially large training dataset is required to train the CNN [13]. We have to reorganize the data and relabel them with two pairs of attributions, i.e., authenticity or forgery, and relevance or irrelevance. The training of the CNN consists of two stages: the initialization stage, and the fine-tuning stage. The initialization stage is utilized to set the initial weights of a network model that has been pretrained with a base dataset to prevent the network model from using any weight learned from other setups in the beginning. The fine-tuning stage includes a supervised learning process, which adjusts the obtained values of parameters in the initialization stage to improve the recognition accuracy and meet the data validation requirement.

In the initialization stage, supervised learning such as the greedy layer-wise training algorithm is adopted to train the CNN based on the specified input-output pairs. In the greedy layer-wise training algorithm, the layers of the CNN are trained in a one-by-one fashion, that is, a hidden layer can be trained if and only if the training of its previous layer has been finished. Furthermore, if the base dataset is significantly larger than the target dataset, transfer learning can be employed to avoid overfitting. In transfer learning, a base network is first trained based on the base dataset, and then part of the layers are transferred to the target network. Afterward, the remaining layers of the target network are randomly initialized and trained toward the new task based on the target dataset.

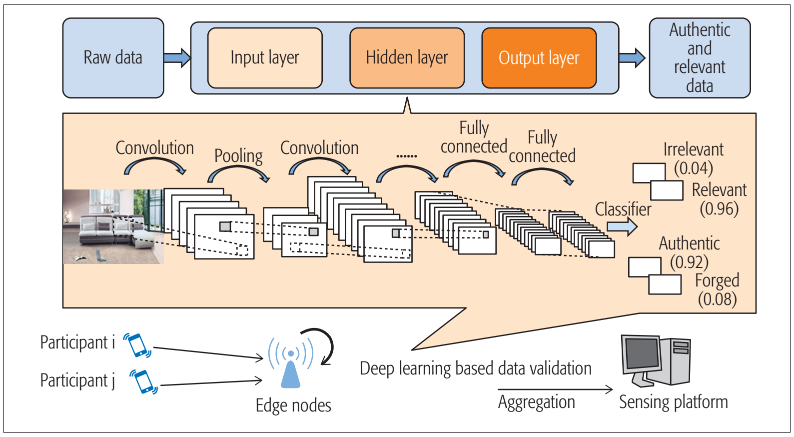

FIGURE 2. The proposed deep learning based data validation and the edge-computing based implementation.

In the fine-tuning stage, the errors from the new task can be back propagated to fine-tune the layers toward the new task. If transfer learning is used in the initialization stage, an alternate approach to the back propagation algorithm is to freeze the transferred features and only train the remaining layers during the training on the new task. The reason for this is that if the target dataset is significantly smaller than the base dataset, the transferred features are left frozen in order to avoid overfitting.

When the difference between the output of the target network and the given output is smaller than the specified threshold, the training of the CNN is completed. After the training process, the CNN is able to automatically detect forged and irrelevant images to guarantee system robustness. In its first layer, the edges can be detected from raw pixels, based on which simple shapes can be detected. Then, higher-level features such as the shape of an object can be learned. In the final layer, these high-level features, which are key to detect forged and irrelevant data, are exploited by a classifier, such as a support vector machine (SVM), Softmax, and so on [6]. As a result, only data that are qualified, unforged, and relevant with regards to the sensing tasks can be preserved.

Edge Processing

The drawback of deep learning is the high computational complexity. In the conventional cloud computing paradigm, deep learning is implemented at remote cloud servers owned by the sensing platform. Therefore, all the raw data are first transmitted from multiple sensor nodes to the base station (BS), and then the BS forwards the raw data to the sensing platform for advanced processing

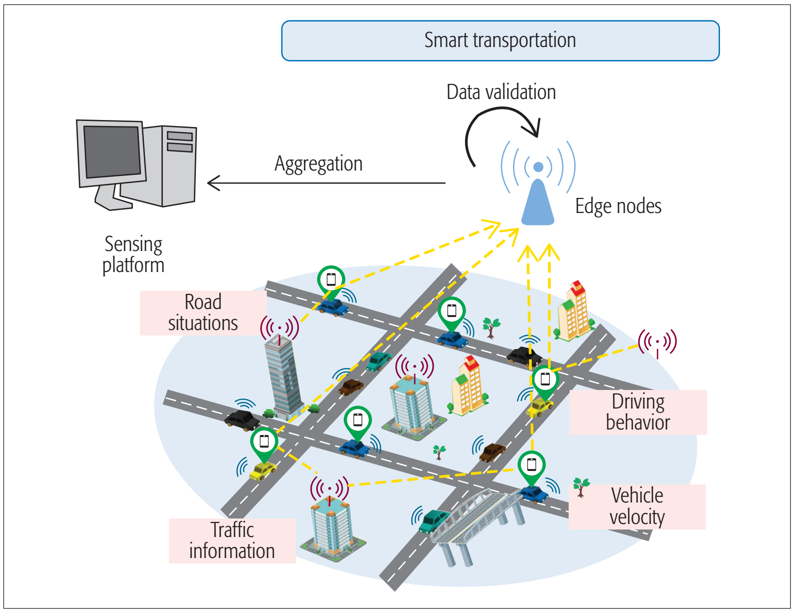

FIGURE 3. Smart transportation system.

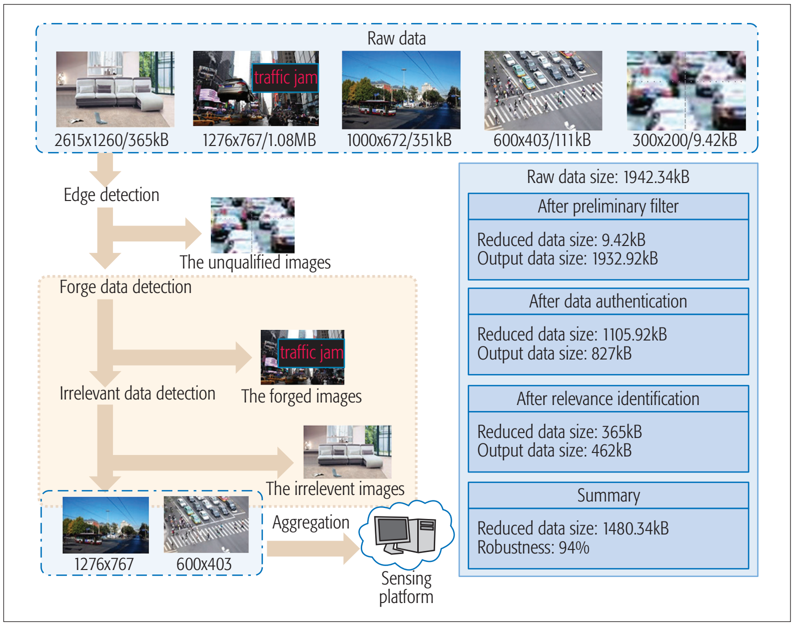

FIGURE 4. Scheme of deep learning based image data validation.

[14]. A critical challenge is that the amount of raw data such as images or video clips can be prohibitively large. As a result, the direct transmission of such a large volume of raw data will not only consume a lot of communication resources, but also cause high transmission latency [13]. To this end, we propose an edge computing-based data processing approach for the RMCS framework, where the raw data such as images or video clips are processed at edge nodes. As shown in Fig. 2, by implementing preliminary filtering, data authentication verification and relevance identification at the network edge, unqualified, forged, and irrelevant data will be detected and filtered out, and only the useful sensory data that are preserved will be aggregated and uploaded to the sensing platform. In this way, the total amount of data that have to be delivered to the sensing platform can be significantly reduced.

Case Study

In this section, a case study of smart transportation shown in Fig. 3 is conducted to evaluate the performance of the proposed RMCS framework. First, RVRP auction based active participant recruitment is carried out, and a pre-contract between the participants and the sensing platform has been specified. Then, each participant has to collect a variety of data, including both the macro descriptions of user surroundings such as traffic information and road conditions, and the micro description of vehicle velocity and driving behavior. To avoid unnecessary rewards and degraded sensing performance, all the raw data must be validated before they can be delivered to the sensing platform. Since most participants use smartphones to take photos and upload data to the sensing platform, only image-data validation is considered here for the purpose of simplicity.

Furthermore, we set three targeted locations and vary the number of potential participants in each location in order to obtain an unbalanced distribution. The number of users at area 1, 2, and 3 are 3, 9, and 27, respectively. The value of the reservation price is 0.5, which presents the mean value of participants' bids. We repeat each simulation more than 10,000 times and compare the proposed scheme with a fixed reward scheme.

To detect forged and irrelevant data, a sufficient training set is required for the CNN, which can be obtained from available datasets such as ImageNet and COCO [15]. Without loss of generality, stochastic operations, e.g., rotation, shearing, and black occluder, are utilized to randomly modify data authenticity and generate forged data required for training. Afterward, based on the two dimensions of authenticity and relevance, data are separately labeled and divided into four classes: forged, unforged, relevant, and irrelevant data. We can also extract the relevant traffic data and relabel them with a semantic description to improve the training performance.

In the training phase, we adopt transfer learning for initialization, followed by the back propagation algorithm to perform the fine-tuning. The first *n* layers of a base neural network, e.g., the weights of ResNet-50 layers which are pre-trained on the ImageNet dataset, are transferred to the target network to implement the new task. In the fine-tuning process, the errors are back propogated to fine-tune the remaining layers of the target network toward the new task, while the first *n* layers are frozen to solve the overfitting problem. An alternate solution to avoid overfitting is to expand the target dataset and decrease the number of parameters, and then all the layers can be fine-tuned toward the new task without concerning about frozen layers. The fine-tuning process is repeated until the difference between the network output and the target output is small enough, and the training phase is completed.

One potential drawback associated with the standard CNN is that all inputs must have the same aspect ratio. To further expand the robustness of the proposed data validation scheme, we have to artificially expand the training dataset by label-preserving image transformations such as rotation and shear.

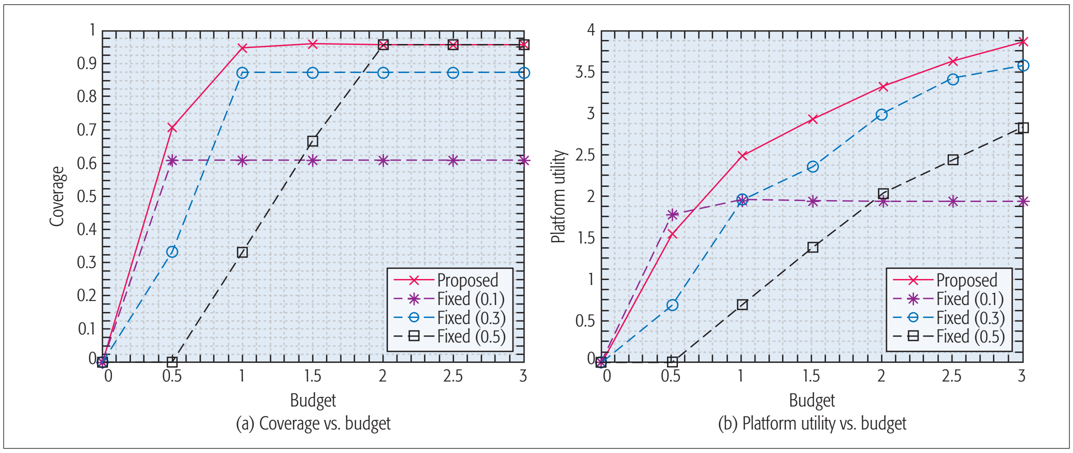

FIGURE 5. Numerical results.

Figure 4 shows how the unqualified, forged, and irrelevant data are filtered out by the proposed deep learning based data validation scheme. The initial size of the input raw data is 1942.34 kB. After preliminary filtering, data authentication verification, and data irrelevance identification, the total size of qualified, unforged, and relevant data are only 462 kB, i.e., 1480.34 kB of data have been filtered out in the edge. Robustness is defined as the percentage of useful data in the total collected data. After data validation, the robustness has been improved from 72 percent to 94 percent.

Figure 5a shows the impact of budgets on sensing coverage for different fixed rates. Similarly, sensing coverage also increases as the budget increases. However, there exists a coverage floor for each scenario. The reason is that the fixed compensation can only meet the requirements of some equipment owners to participate in the sensing activities. The higher the fixed reward, the higher the final sensing coverage will be. What's more, when it is at 0.5, the sensing coverage is even 0 at low budgets. As shown in the figure, our proposed scheme can stimulate more device owners to participate in sensing activities with lower budget than the fixed award scheme, which eventually achieves a higher sensing coverage.

Figure 5b shows the sensing platform utility versus the budget. The platform utility increases as the budget increases. Furthermore, numerical results demonstrate that the proposed scheme provides better performance than other schemes. The reason is that the platform can obtain more information about the users as all of them reveal the true private cost by an auction-based mechanism which indicates that the platform can maximize the payoff by setting a reasonable reward. Hence, simulation results confirm that the proposed RMCS architecture yields significant enhancement in sensing accuracy and platform utility.

Research Challenges and Open Issues

Although the proposed architecture provides benefits in many aspects, it still faces several challenges during practical implementation.

Security and Privacy

The user equipment faces numerous security threats including data loss, unauthorized access, malware, electronic eavesdropping, server resident data, and so on. Also, compared with a laptop or a notebook computer, a mobile device is easier to lose. Once a mobile device falls into the wrong hands, the information stored in it can be easily obtained, and will be misused to launch attacks on MCS servers. The problem of how to leverage deep learning to detect potential threats requires further exploration.

The collected data of the surrounding environment will change rapidly and vastly when the devices move from indoors to outdoors. The sudden change of environment requires a large amount of training data to retrain the deep learning system for data correction, which requires further investigation.

Computational Overhead

Deep learning is data-driven and requires a large amount of training data. Hence, there exists an obvious gap between the training data set and the practical data set, and the performance of a trained deep learning system degrades when it is applied in the real world. The discrepancy between training data and practical data becomes more obvious when the environment of devices changes dynamically. For example, the collected data of the surrounding environment will change rapidly and vastly when the devices move from indoors to outdoors. The sudden change of environment requires a large amount of training data to retrain the deep learning system for data correction, which requires further investigation.

Energy Efficiency

To reduce the burden on backhaul links, deep learning can be implemented in mobile devices to detect unqualified, forged, and irrelevant data. However, the implementation of a deep learning system requires high computing capability, which leads to increased energy consumption. There exists an obvious challenge to implement deep learning in mobile devices simply because such devices are not equipped with sufficient battery capacity. Hence, it is urgent to develop an energy efficient deep learning approach that can be implemented in mobile devices.

Conclusions

In this article, we proposed an RMCS framework to guarantee reliable service delivery and cost-efficient operation for MCS systems. First, we presented a thorough literature review. Then, the

To reduce the burden on backhaul links, deep learning can be implemented in mobile devices to detect unqualified, forged, and irrelevant data. However, the implementation of a deep learning system requires high computing capability, which leads to increased energy consumption.

architecture and the implementation of RMCS were introduced. We proposed an RVRP auction based active participant recruitment scheme, which is incentive compatible and can maximize the platform utility under the scenario of information asymmetry. Furthermore, a CNN based forged data and irrelevant data detection scheme was proposed, and an edge computing based local process was utilized to reduce traffic load and transmission latency. Next, we developed a case study of smart transportation to demonstrate the robustness and efficiency of the proposed RMCS framework. Finally, simulation results confirmed that the proposed framework yields satisfactory performance in improving sensing platform utility and data accuracy.

Acknowledgments

This work was partially supported by the Beijing Natural Science Foundation under grant number 4174104; the National Natural Science Foundation of China (NSFC) under grant number 61601181; the Fundamental Research Funds for the Central Universities under grant number 2017MS001; and Beijing Outstanding Young Talent under grant number 2016000020124G081.

References

[1] J. Huang *et al.*, "A Novel Deployment Scheme for Green Internet of Things," *IEEE Internet Things J.*, vol. 1, no. 2, Apr. 2014, pp. 196–205.

[2] L. Xiao *et al.*, "A Secure Mobile Crowdsensing Game with Deep Reinforcement Learning," *IEEE Trans. Info. Forensics Security*, vol. 13, no. 1, Aug. 2017, pp. 35–47.

[3] "Sensorly: Unbiased Wireless Network Information," http://www.sensorly.com/, accessed: 2017-05-14.

[4] P. Mohan *et al.*, "Nericell: Rich Monitoring of Road and Traffic Conditions Using Mobile Smartphones," *Proc. 6th ACM Conf. Embedded Network Sensor Systems*, ser. SenSys '08. New York, NY, USA: ACM, 2008, pp. 323–36; available: http://doi.acm.org/10.1145/1460412.1460444

[5] D. Peng *et al.*, "Data Quality Guided Incentive Mechanism Design for Crowdsensing," *IEEE Trans. Mobile Comput.*, vol. PP, no. 99, June 2017, pp. 1–1.

[6] Z. M. Fadlullah *et al.*, "State-of-the-Art Deep Learning: Evolving Machine Intelligence Toward Tomorrow's Intelligent Network Traffic Control Systems," *IEEE Commun. Surveys Tuts.*, vol. 19, no. 4, May. 2017, pp. 2432–55.

[7] X. Chen *et al.*, "Exploiting Massive D2D Collaboration for Energy-Efficient Mobile Edge Computing," *IEEE Wireless Commun.*, vol. 24, no. 4, Aug. 2017, pp. 64–71.

[8] S. Gisdakis *et al.*, "Security, Privacy, and Incentive Provision for Mobile Crowd Sensing Systems," *IEEE Internet Things J.*, vol. 3, no. 5, Oct. 2016, pp. 839–53.

[9] N. Line, *et al.*, "Can Deep Learning Revolutionize Mobile Sensing?" *Proc. HotMobile '15*, Santa Fe, New Mexico, USA, Feb. 2015, pp. 117–22.

[10] S. Yao *et al.*, "DeepSense: A Unified Deep Learning Framework for Time-Series Mobile Sensing Data Processing," *Proc. WWW '17*, Perth, Australia, Nov. 2016, pp. 351–60.

[11] S. Basudan *et al.*, "A Privacy-Preserving Vehicular Crowdsensing-Based Road Surface Condition Monitoring System Using Fog Computing," *IEEE Internet Things J.*, vol. 4, no. 3, Feb. 2017, pp. 772–82.

[12] A. Rahman *et al.*, "Towards a Secure Mobile Edge Computing Framework for Hajj," *IEEE Access*, vol. 5, no. 99, Jun. 2017, pp. 11768–81.

[13] H. Li *et al.*, "Learning IoT in Edge: Deep Learning for the Internet-of-Things with Edge Computing," *IEEE Network*, vol. 32, no. 1, Jan. 2018, pp. 96–101.

[14] J. Huang *et al.*, "Topology Control for Building a Large-Scale and Energy-Efficient Internet of Things," *IEEE Wireless Commun.*, vol. 24, no. 1, Feb. 2017, pp. 67–73.

[15] K. He *et al.*, "Deep Residual Learning for Image Recognition," *CVPR*, June 2016, pp. 770–78.

Biographies

Zhenyu Zhou [M'11, SM'17] received a Ph.D. degree from Waseda University, Japan in 2011. Since March 2013, he has been an associate professor at North China Electric Power University, China. He is an editor for *IEEE Access*, *IEEE Communications Magazine*, and a workshop co-chair for IEEE ISADS'15 and Globecom'18, among others. He received the 2017 IET Premium Award, and the IEEE ComSoc GCCTC 2017 Best Paper Award. His research interests include green communications and vehicular communications.

Haijun Liao is working toward the M.S. degree at North China Electric Power University, China. Her research interests include deep learning and smart grid.

Bo Gu [M'13] received the B.E. degree from Tianjin University, Tianjin, China, in 2004, the M.E. degree from Peking University, Beijing, China, in 2007, and the Ph.D. degree from Waseda University, Tokyo, Japan, in 2013. Since 2016, he has been with the Department of Information and Communications Engineering, Kogakuin University. His current research interests include network economics, game theory and network optimization. He is a member of the IEICE.

Kazi Mohammed Saidul Huq [SM'17] (kazi.saidul@av.it.pt) received the B.Sc. degree in computer science and engineering from Ahsanullah University of Science and Technology, Bangladesh, in 2003; the M.Sc. and Ph.D. degrees in electrical engineering from Blekinge Institute of Technology, Sweden in 2006 and the University of Aveiro, Portugal in 2014, respectively. He is currently a researcher with the Instituto de Telecomunicações—Aveiro, Portugal. He is a founding member of the IEEE 1932.1 Standard for Licensed/Unlicensed Spectrum Interoperability in Wireless Mobile Networks. His research activities include 5G paradigm, backhaul/fronthaul, mmWave, THz, and green radio.

Shahid Mumtaz [SM'16] (smumtaz@av.it.pt) received his M.Sc. degree from Blekinge Institute of Technology, Sweden, and his Ph.D. degree from the University of Aveiro, Portugal. He is currently a senior research engineer with the Instituto de Telecomunicações Pólo de Aveiro, Portugal, where he is involved in EU funded projects. His research interests include MIMO techniques, multihop relaying communication, cooperative techniques, cognitive radios, game theory, and energy-efficient frameworks for 5G. He has authored several conference papers, journals, and books.

Jonathan Rodriguez [SM'13] (jonathan@av.it.pt) received his Master's degree in electronic and electrical engineering and Ph.D. from the University of Surrey, United Kingdom, in 1998 and 2004, respectively. In 2005, he became a researcher at the Instituto de Telecomunicações with key interests in 5G mobile systems. He is an author of more than 400 scientific works, and a Fellow of the IET. Since 2017, he has been a professor of mobile communications at the University of South Wales, United Kingdom.