2014 IEEE NINTH INTERNATIONAL CONFERENCE ON INTELLIGENT SENSORS, SENSOR NETWORKS AND INFORMATION PROCESSING (ISSNIP)
SYMPOSIUM ON PARTICIPATORY SENSING AND CROWDSOURCING
SINGAPORE, 21–24 APRIL 2014

A Generic Participatory Sensing Framework for Multi-modal Datasets

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***Abstract*—Participatory sensing has become a promising data collection approach to crowdsourcing data from multi-modal data sources. This paper proposes a generic participatory sensing framework that consists of a set of well-defined modules in support of diverse use cases. This framework incorporates a concept of "human-as-a-sensor" into participatory sensing and allows the public crowd to contribute human observations as well as sensor measurements from their mobile devices. We specifically address two issues: *incentive* and *extensibility*, where the former refers to motivating participants to contribute high-quality data while the latter refers to accommodating heterogeneous and uncertain data sources. To address the incentive issue, we design an incentive engine to attract high-quality contributed data independent of data modalities. This engine works together with a novel social network that we introduce into participatory sensing, where participants are linked together and interact with each other based on data quality and quantity they have contributed. To address the extensibility issue, the proposed framework embodies application-agnostic design and provides an interface to external datasets. To demonstrate and verify this framework, we have developed a prototype mobile application called *imReporter*, which crowdsources hybrid (image-text) reports from participants in an urban city, and incorporates an external dataset from a public data mall. A pilot study was also carried out with 15 participants for 3 consecutive weeks, and the result confirms that our proposed framework fulfills its design goals.**

Keywords: Crowdsourcing, participatory sensing, pervasive computing, incentive mechanism, social network.

I. Introduction

Modern mobile devices with a variety of built-in sensors have enabled the confluence of ubiquitous computing, networking technologies, distributed decision making, and wireless sensor networks. Emerging on this trend is participatory sensing, which crowdsources sensory measurements from mobile devices owned by public crowd, and has become a promising approach to large-scale and multi-modal data collection [1][2][3][4][5][6]. Waze [1] provides a travel navigation system using GPS information collected from smartphones and vehicles. Steptacular [2] allows participants to upload their pedometer readings into a database and awards them credits based on the number of steps they have taken. Apollo [3] proposes a sensor information processing tool for uncovering likely facts from noisy participatory sensing data. In NoiseTube [4], citizens can measure their sound exposure in their everyday life using their mobile phones, and participate in creating a collective map of noise pollution by sharing geolocalized measurements with the participatory community.

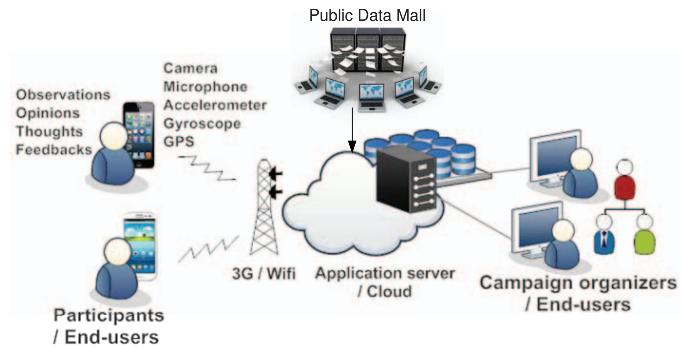


Fig. 1. Overview of a generic participatory sensing system.

Other smartphone applications [5] [6] exploit crowdsourced data for environmental improvements. On the other hand, there are public datasets provided by government authorities to facilitate livability and sustainability in urban areas. For example, Singapore Land Transportation Authority provides periodic video stream captured by pre-deployed cameras at some particular road segments [7]. We envisage that the next-generation participatory sensing systems should be able to handle the confluence of multi-modal and uncertain data from various crowd-powered sources and several public datasets simultaneously in order to provide diverse functionalities and enriched information.

In this paper, we propose a generic participatory sensing (gPS) framework which consists of multiple functional modules that are independent of specific applications and can accommodate multi-modal data sources. This framework incorporates a concept of "human-as-a-sensor" into the participatory sensing paradigm to collect human observations, in addition to sensor measurements, from mobile devices owned by the public crowd. Fig. 1 gives the overview of such a gPS system, which we describe below using an example use case in transportation. The organizers launch a city-wide data collection campaign of transportation activities for urban planing. Each participant carries a mobile device to report measurements from the built-in accelerometer, gyroscope, and GPS sensor, which can be used to deduce his travel mode (e.g., by car or foot) and travel speed, as well as to report images using the built-in camera, which may serve as witness of traffic accidents. A participant can also annotate the images and write text-based feedback on city transportation systems. These reports are then sent to a back-end application server or a cloud via WiFi/3G/4G connections. In addition to these crowdsourced dynamic traffic information, some relatively static video streams which are captured at road junctions and stored in a public data mall, can also be fed into the back-end cloud. The campaign organizers, who may also be end-users, can then extract useful information from the combination of dynamic crowdsourced content and static database to figure out the actual traffic situations and make more informed decisions.

In participatory sensing, two critical challenges arise: *incentive* [8][9] and *extensibility*. The former refers to motivating the public crowd to contribute data from their mobile devices, while the latter refers to providing an elastic framework for diverse and uncertain data sources. To address the incentive issue, our proposed gPS framework embeds an incentive engine working together with an endorsement social network, which exploits mutual influence among participants by allowing them to interact with each other based on the quality and quantity of their contributed data. To address the extensibility issue, the gPS framework features application-agnostic design in support of diverse use cases and multi-modal datasets, and allows for interfacing with external datasets as well.

To demonstrate and verify our proposed gPS framework, we design and implement a prototype application called *im-Reporter*, which allows participants to report various urban issues in their daily life in order to improve the livability of urban cities. We have also conducted a pilot study with 15 participants for 3 consecutive weeks, and present the results in this paper.

The remainder of this paper is organized as follows. We review related work in Section II, and explain the design details of the gPS framework in Section III. Section IV describes our prototype and pilot study. Section V concludes this paper.

II. Related Work

Smartphone-based sensing technologies combined with data analytics has steered data collection towards a new sensing paradigm, participatory sensing [10]. Using vehicle-equipped GPS sensors or smartphones to collect daily mobility information has attracted a lot of attention and created many promising applications. Work [11] infers users' transportation modes. By collecting real-time GPS locations of cars, [12] shows how to mine the current traffic conditions of road segments such as waiting time at intersections. Based on GPS and WiFi data collected by vehicles, [13] designs a real-time traffic monitoring system to estimate the travel delays on road segments, where coexisting GPS and WiFi sensing data are collected periodically. Reference [14] uses smartphones to track people who are on a bus. To determine whether a user is on a bus, the work matches the user's trajectory with the features of buses' schedules. To track daily trajectories, reference [15] proposes an adaptive GPS duty-cycle scheduling scheme to allocate limited energy of a smartphone to the GPS sensor. Reference [16] designs a system to conduct transit tracking and predict the bus arrival time. Based on the color of traffic signals detected by a smartphone, in [17], advice on driving speed is provided to reduce the vehicle fuel consumption.

Instead of positioning using absolute GPS coordinates, several efforts focus on discovering meaningful places

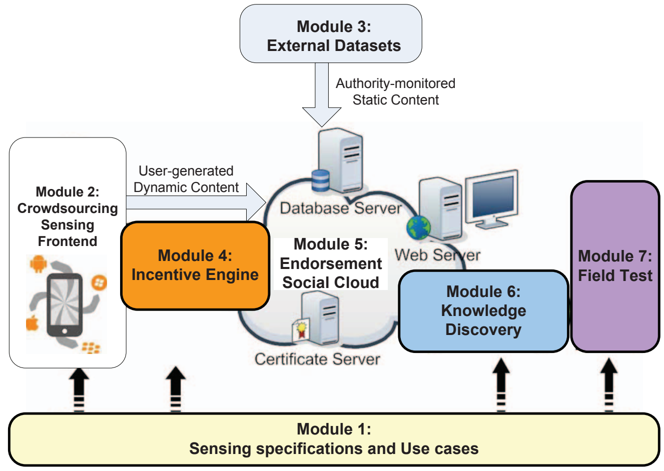


Fig. 2. The generic participatory sensing framework for multi-modal data.

[18][19][20][21][22][23]. Based on GPS fixes, a density-based clustering algorithm is proposed to recognize meaningful places [18]. Using a set of radio beacons to define a physical space is proposed in [19]. In [20], a remote server identifies ambient fingerprints of places and performs fingerprint filtering and matching to conduct localization. Based on the patterns of changes in ambient network signals, the back-end server analyzes data collected by smartphones to discover places visited by users [21]. To reduce energy consumption of smartphones, in [22], users manually label some places discovered by smartphones so as to avoid using GPS in labeled places. In [23], users are allowed to verify those places learned by smartphones or define a new place manually.

To address energy issue, [24] proposes Piggyback Crowd-Sensing, a system that collects mobile sensor data from smartphones in order to lower down the energy overhead of user participation. The main idea is to collect and mine sensor data so as to identify and exploit the timing of smartphone users having phone calls or using phone apps. Reference [25] creates an activity diary with searchable database of locations and activities using GPS data streams generated by users' phones. In [26], a crowdsensing test-bed is designed for capturing and processing events affecting citizens in a city.

In our work, instead of giving a specific participatory sensing application, we propose a generic end-to-end framework that integrates user interface, incentive mechanism, data analytics with massive data streams and diverse modalities of digital information being captured at an incredible rate.

III. Generic Participatory Sensing Framework

Fig. 2 gives our end-to-end gPS framework which contains seven modules. We explain each module in detail as follows.

Module 1: Sensing specifications and use cases. This module identifies the sensing needs and the basic functionalities for any specific applications which may be defined by the campaign organizers and application developers (manually or through a formal language such as XML). Specifically, this module defines the data format for heterogeneous types of sensors, the types of participants, the required sampling rate for each type of sensors, the requirements of data visualization and representation, and the number of expected participants for cloud provisioning that deals with the system-level scalability on back-end servers.

Module 2: Crowdsourcing sensing frontend. This module provides participants with a cross-platform user interface for reporting crowdsourced data. Specifically, we incorporate the concept of "*human-as-a-sensor*" into the sensing scheme, where a participant can submit his/her in-situ observations and opinions which incorporate human intelligence as well as heterogeneous data modalities and measurements from diverse sensor sources. Compared to the purely sensor-based and continuous-sensing approach, this sensing module conducts intermittent and on-demand sensing that allows users to determine the sensing timing, thereby reducing energy consumption in sensing. A user also has the option to allow whether to expose his/her location information, which helps protect user privacy. To improve the usefulness of collected data, a data validation phase is also integrated to check the data integrity and filter out redundant data before uploading.

Module 3: External datasets. As some government authorities or agencies have provided open data malls, this module allows sensing data from external datasets to be incorporated into the system to enrich the functionalities and services. With the input from these external datasets, the system will be able to provide a mixture of the user-generated content collected by Module 2, which is usually captured by participants dynamically, and the authority-monitored content collected by this module, which is usually captured at some particular locations periodically. For example, the Land Transport Authority (LTA) of Singapore publishes several transport-related datasets for public downloads and can be used to create and test innovative applications by third parties. One of these datasets, for instance, is the traffic-related dataset including availability and charges of parking lots, camera images along expressways and checkpoints as well as traffic information. The traffic-related dataset is static since it is periodically updated at a fixed sampling interval of 5 minutes and the images are captured at particular checkpoints along some important road segments. Compared to such periodic and static datasets, crowdsourced datasets are more dynamic as the data is collect at anytime anywhere. With the combinations of static and dynamic data sources, the framework can enrich the services of the designed application systems.

Module 4: Incentive engine. This module aims to encourage participants to contribute more and high-quality data. It rewards each participant based on the quality and quantity of data contributed by the participant, where the reward can be monetary [9] or non-monetary [8] (e.g., service time quota in a traffic navigation application for accessing the navigation service provided by the system). Specifically, in the incentive scheme, each participant is associated with a contribution power (CP) which indicates the contribution performance of the participant. For illustration purposes, we simply define the CP of participant i as $CP_i = \sum_{k=1}^{N} q_k \cdot a_k$, where N is the number of pieces of data submitted by i, q_k is the data quality [27][1] for the k-th piece of data, and a_k is the data size for the k-th piece of data. This simple formulation will be refined later in Module 5. Here the evaluation of data quality can be performed by a text mining and/or image analyzing process, or a trust score assignment algorithm. The system can then reward the participant according to a function $R(CP_i) = \alpha \cdot CP_i^{\beta} + \gamma$, where $\alpha > 0$ and $\beta > 0$ are predefined parameters, and γ is the initial credit allocated to the participant.

[1]As there might be interdependency between different pieces of data, spatiotemporal correlation may be considered to evaluate data quality.

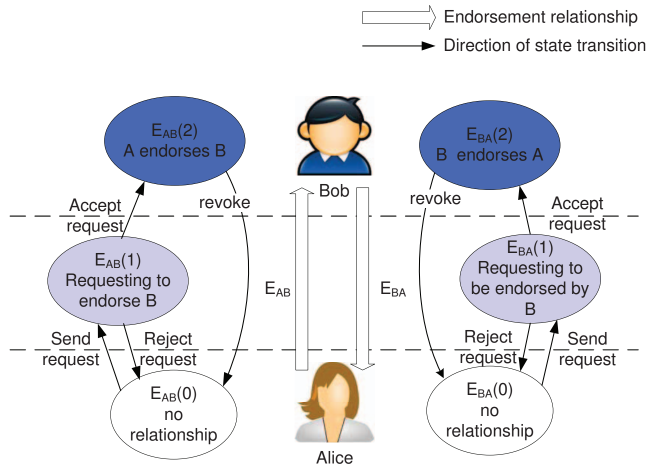


Fig. 3. The state transition of endorsement.

Module 5: Endorsement social cloud. Together with the incentive engine, the framework incorporates a novel social network in the cloud, called an *endorsement social network*, to enhance the incentive effect by exploiting the *mutual influence* among participants. It links participants based on whether a participant trusts the data contributed by another. Compared with the bidirectional friendship in conventional social networks (e.g., facebook and LinkedIn), the social relationship in the endorsement social network is directed. For any two participants, say Alice and Bob ("A" and "B" for short), there are two possible endorsement relationships between them, E_{AB} and E_{BA}, where E_{AB} indicates A is endorsing B while E_{BA} indicates B is endorsing A. Note that E_{AB} and E_{BA} do not necessarily co-exist; E_{AB} is created only when A is willing to endorse B, and vice versa. There are three states of the endorsement relationship from A to B, denoted by $E_{AB}(j)$, $j = 0, 1, 2$, and similarly is E_{BA}. Fig. 3 shows the states transition (between state 0, state 1, and state 2) of endorsement relationship between two participants. Initially, E_{AB} and E_{BA} are at state 0 which means no endorsement relationship between them. If participant A trusts the data submitted by participant B, participant A can send a request to endorse participant B. Then, E_{AB} will transit to state 1 which indicates waiting for acceptance from participant B. If participant B rejects the request from A, E_{AB} will transit back to state 0. If he accepts the request from participant A, E_{AB} will transit to state 2 which means that the relationship of A endorsing B is established. Afterward, participant A may revoke endorsement relationship E_{AB} anytime when he witnesses that participant B submits falsified data, in which case E_{AB} will transit to state 0 again. For E_{BA}, the similar process applies and is depicted in the same diagram. Now, with the introduction of this endorsement social network, we

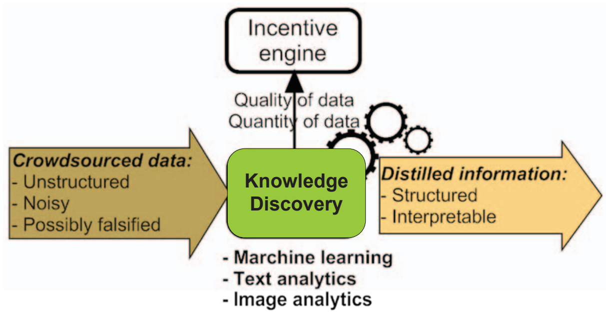


Fig. 4. The workflow of knowledge discovery module.

can refine the contribution power in Module 4 as

$$CP_i = \sum_{j=1}^{M} \mathbb{1}_{E_{ji}(2)} \cdot CP_j \cdot \sum_{k=1}^{N} q_k \cdot a_k,$$

where $\mathbb{1}_A$ is the indicator function which equals 1 when A is true and equals 0 otherwise, M is the total number of participants in the system. It shows that participants who are endorsed by more and "powerful" users are also tend to be trusted more by the system, where a user's credibility in the system (i.e., contribution power) is built either by the mutual trust among participants or through other participants verifying reports at originating locations.

Module 6: Knowledge discovery. In a crowdsourcing system, the submitted data may be unstructured, noisy, and falsified. In this regard, Module 6 provides intelligent data processing capability using machine learning, text mining, and image processing techniques to extract and reconstruct useful information from the raw sensing data submitted by participants. With the intelligent data processing and analytics technologies, the quality of crowdsourced data can also be evaluated and fed back to Module 4 (the incentive engine) to optimize the rewards. This module thus converts raw data streams coming from the front-end clients into structured and interpretable information, and also provides useful feedback to aid the system to make more informed decisions and enhance data trustworthiness. For example, mobility-based applications may need to combine location data from different sources (e.g., GPS and network-based positioning technologies) and cluster them into a single absolute location. Based on the localization accuracy, this module will closely work with our application-independent modules, the incentive engine and the endorsement social cloud, to provide feedback of data quality for the system.

Module 7: Field test. This module integrates all of modules into a real-world participatory sensing system to carry out pilot studies at different sales by different groups of participants. Testing scenarios provided by the campaign organizers can be used to verify the performance of designed algorithms and methodologies for different modules.

IV. An Application Example: imReporter

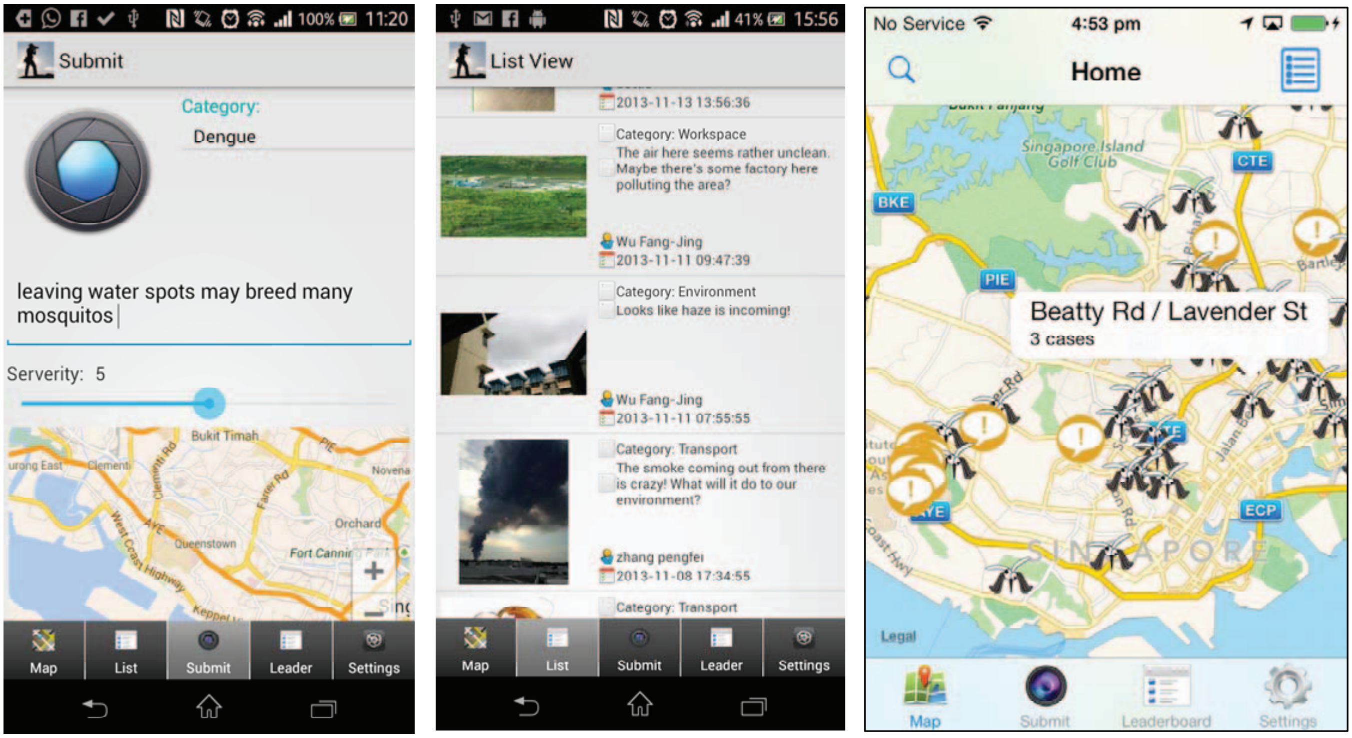
In this section, we design a potential use case of our proposed gPS framework which allows participants to report everyday issues (for example, unhandled mosquito breeding spots, bus breakdowns, or environmental uncleanliness). We have developed a crowdsourcing system based on the gPS framework, with a front-end tailored for both Android-based and iOS-based smartphones. With this application, which we call *imReporter*, each participant acts as a reporter to report events related to issues mentioned above. Each report contains the following information: (1) event category, (2) a photo of the event, (3) a short description of the event, (4) the severity level of the event, (5) the name of the reporter, (6) the timestamp of the event, and (7) the location of the event. Here, the location information is obtained from either GPS information or WiFi localization techniques, depending on the signal availability. We have implemented our back-end modules and host them in the Amazon Elastic Compute Cloud (Amazon EC2) [28]. In the incentive engine, the default values for parameters are $\alpha = 1$, $\beta = 1$, and $\gamma = 10$.

We consider a real-world campaign against dengue in Singapore [29]. Since dengue fever is the most common mosquito-borne viral diseases in the world, the National Environment Agency (NEA) in Singapore launched the campaign officially on 28 April 2013. The campaign aims to promote awareness on the dengue situation, inspire actions to prevent dengue, and encourage advocacy through social media and word of mouth. It was launched at a time when community support was and continues to be critical to stop the chain of dengue transmission. Motivated by the needs of this campaign against dengue, which calls on as many citizens as possible to do their part, we developed the end-to-end participatory sensing system to demonstrate our gPS framework, where crowdsourced reports from participants as well as public datasets of dengue clusters from NEA (data.gov.sg) are both incorporated into the system.

Fig. 5 shows some representative screenshots of our front-end mobile application, where Fig. 5(a) allows a participant to submit a report, and Fig. 5(b) displays the list of reports submitted by all the participants. In Fig. 5(c), the small yellow bubbles indicate the crowdsourced dengue spots from participants' smartphones, while the mosquito-like icons indicate the data points from the external dataset, i.e., the dengue clusters provided by NEA. These two datasets thus complement each other and thereby provide a more comprehensive view of the dengue situation of Singapore.

Our incentive engine computes the value of CP for each participant and the endorsement social cloud corroborates it with participants' endorsement decisions. In Fig. 6(a), the values of CP are sorted in descending order and can be viewed on each particpant's smartphone as a "leaderboard". Fig. 6(b) gives a snapshot of the endorsement relationship between participants, where the current logged-in user can see if he/she is endorsing, or is endorsed by, the participant on the screen. He/she can also interact with the participant on the screen by sending out endorsement requests or revoke existing endorsement relationships. With the endorsement social cloud, the system links users together based on the quality and quantity of their contributed data.

With this imReporter mobile application as well as the back-end module support, we have conducted a pilot study with 15 participants for 3 weeks, and received a total of 77 reports during the period. Fig. 7 provides the statistics of this pilot study, where the participants' rewards are sorted in ascending order. As we can see, a participant gets a larger



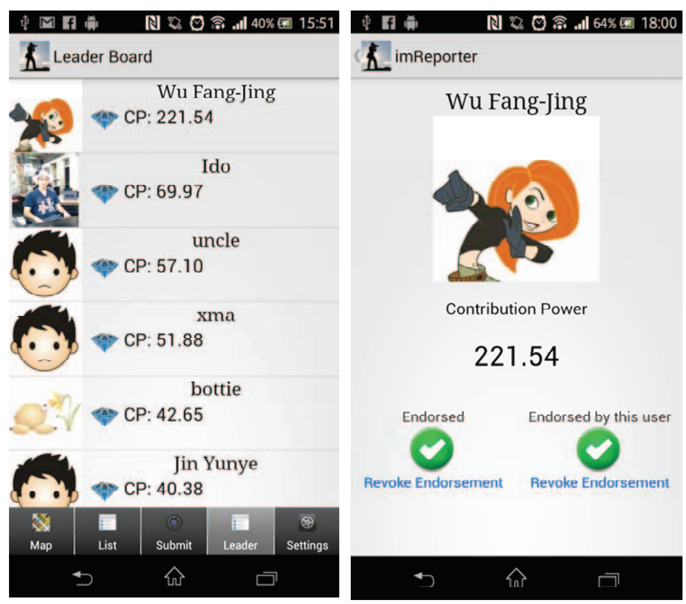
(a) (b) (c)

Fig. 5. User interfaces of imReporter.

reward $R(CP_i)$ if he/she contributes more reports. Participants who do not contribute reports (users 1-4) will only have the default initial reward of 10. As it can be seen in the pilot study, our incentive engine and the endorsement social network are able to encourage participants to contributed data with the CP and the rewards are evaluated. As the incentive engine and the endorsement social network are application-agnostic, the system can be easily extended to other applications by primarily modifying the sensing frontend.

V. Conclusion

This paper provides a generic participatory sensing framework that designs application-agnostic modules for accommodating multi-modal data stream from various data sources. Since the sensing data may come from mobile devices with any human life-loggers, sensor-equipped vehicles, smart cards, and social network services, we incorporate a concept called "human-as-a-sensor" into the proposed framework to source for both human observations and sensor data from public crowd via their mobile devices. The proposed framework addresses end-to-end issues from the front-end crowdsourced sensing modules and external data sources towards the incentive modules, knowledge discovery modules, and endorsement social cloud on the back-end servers. To demonstrate how the proposed framework works and how it facilitates the design of participatory sensing applications, we have developed an example mobile application system and carried out a pilot study. Our future work includes enhancing the incentive engine with more sophisticated design, and rolling out a pilot study at a much larger scale. contributions when different groups of participants are considered.



(a) (b)

Fig. 6. User interfaces of the incentive scheme in imReporter.

Acknowledgment

This research is supported by the Generalized Participatory Sensing (g-PS) project with grant number 1224104046 through the Science and Engineering Research Council (SERC), Agency for Science, Technology and Research (A*STAR). The

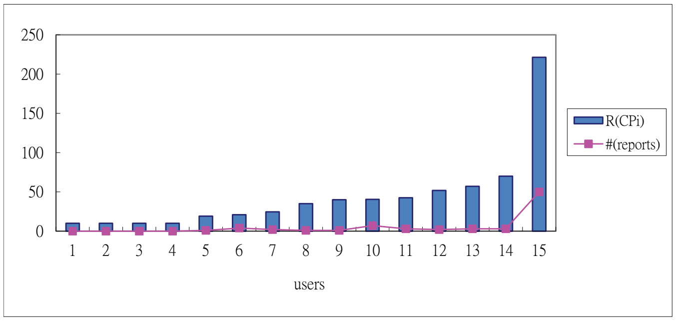


Fig. 7. Statistics of the pilot study.

authors are grateful to Xian You Lim and Shaozhuang Chen for their help and support in the application development process and the pilot study.

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