Crowdsensing in the Wild with Aliens and Micro-payments

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***Abstract*—This article presents results and lessons learned from two user studies on crowdsensing incentives, specifically mobile gaming and micro-payments. The analysis of the results suggests that gaming is a cost-effective solution for uniform area coverage, while micro-payments work well for sensing tasks with tight time constraints or long-term tasks for personal analytics.**

I. Introduction

Mobile crowdsensing can be used to enable a broad spectrum of applications, ranging from monitoring pollution or traffic in cities to epidemic disease monitoring or reporting from disaster situations. Several mobile apps [1] and platforms [2], [3] have recently been proposed for crowdsensing.

A major challenge for broader adoption of mobile crowdsensing apps/systems is how to incentivize people to collect and share sensor data. In addition, uniform sensing across a target area is a desirable property in many cases, and incentives need to be provided to collect data from unpopular regions of that area. Many of the proposed mobile crowdsensing systems provide monetary incentives to smart phone users to collect sensing data. There are solutions based on micro-payments [4] in which small tasks are matched with small payments. Other techniques were also explored to motivate individuals to participate in sensing. For example, beneficial personal analytics are provided as incentives to participants through sharing bicycle ride details in Biketastic [5]. Another variety of incentive is enabling data bartering to obtain additional information (bargain hunting through price queries in LiveCompare [6]). In addition, there are gamification techniques proposed for crowdsourced applications [7].

We recently designed, built, and evaluated through user studies two crowdsensing systems based on different types of incentives: (1) a mobile game that uses in-game incentives to convince participants to cover all the regions of a target area, including the unpopular ones; (2) a micro-payment based system that allows users to pick the sensing tasks they want to execute according to their own criteria and provides a small payment for each task.

Our game, "Alien vs. Mobile User" [8], is a first person shooter sensing game which is played by mobile crowdsensing participants on their smart phones. The game involves tracking the location of extraterrestrial aliens on the campus map of our institution and destroying them. The game entices users to unpopular regions through a combination of in-game incentives, which include alien-finding hints and higher number of points received for destroying aliens in these regions. The game was implemented in Android, and it collects WiFi signal data to construct the WiFi coverage map of the targeted area.

Our micro-payment based system, McSense [3], allows the participants to choose from a wide-range of sensing tasks such as taking photos at events on campus, collecting GPS and accelerometer readings, or collecting application and network usage from the phones. When choosing a task, the participants have to balance the value of micro-payment (different for each task) against their effort, the potential loss in privacy and the resource consumption on the phone (e.g., battery). A McSense application was implemented for Android phones.

This article describes the results and lessons learned from two user studies, one for gaming and one for micro-payments. Any student on campus was allowed to participate in these studies, and all they had to do in order to participate was to install our mobile apps and sign a participant form. Over 50 students participated in each study, and the duration of the studies were 35 days for mobile gaming and two months for micro-payments.

II. Related Work

Micro-payments have been used as an incentive for users to complete tasks in crowdsourcing (e.g., Amazon MTurk - http://www.mturk.com). Micro-payments have also been examined in the context of participatory sensing [4] and crowdsearching [9]. The work in [10] presents pricing incentive mechanisms to collect quality data in participatory sensing applications. Some of the key findings are that incentives can be highly beneficial in recruiting participants and that micro-payments have the potential to extend participant coverage both spatially and temporally. In addition to these insights, our micro-payment based study identifies data reliability as a significant issue in crowdsensing based on micro-payments.

Attracting people to unpopular places could be difficult and expensive. For example, the results from a recent crowdsensing study [11] show that many places will be infrequently visited. Gaming could be a cost effective alternative to micro-payments when attracting users to unpopular regions is necessary.

In the same context, the concept of steered crowdsensing is proposed in [12] to address the data quality issue in crowdsensing. The paper argues that most crowdsensing systems are simply increasing the number of participants in a given area in order to improve data quality; however, this is not efficient when considering monetary incentives. The proposed solution involves a quality indicator which determines the size of the reward received by a participant for collecting data in a given location. In this way, participants can be steered, with higher rewards, to unpopular regions. There is similarity between the mechanism employed in this research and the mechanism we use to attract users to unpopular regions in our game.

While there is a significant literature on using gamification techniques in crowdsourcing, there is very little in terms of applying gamification techniques in mobile sensing. Bud-Burst [7] is a smart phone application for an environmental participatory sensing project. The main goal is "floracaching", for which players gain points and levels within the game by finding and making qualitative observations on plants. Another participatory sensing game, Who [13], is used to extract relationship and tag data about employees. It was found useful for rapid collection of large volumes of high-quality data from "the masses". None of these participatory sensing games addresses the problem of uniform area coverage in the context of crowdsensing, which is a major point in our studies.

Existing work in mobile health such as BeWell [14] utilizes phone sensing to assess the users' wellbeing through scores based on their daily activities. In BeWell, an animated aquatic ecosystem is shown with three different animals, the behavior of each being affected by changes in the user's wellbeing. Thus, the users are motivated to maintain a healthy lifestyle. In a similar direction, our mobile game focuses on utilizing game graphics and in-game incentives to motivate smart phone users for achieving cost-effective crowdsensing.

III. Alien vs. Mobile User Game

The game is a first person shooter game played by mobile users on their smart phones while moving in the physical environment. Since the goal of the game is to uniformly cover a large area with sensing data, it is essential to link the game story to the physical environment. In our game, the players must find aliens throughout an area and destroy them using bullets that can be collected from the target area. The players collect sensing data as they move through the area. Although the game could collect any type of sensing data available on the phones, our implementation collects WiFi data (*BSSID, SSID, Frequency, Signal strength*) to build a WiFi coverage map of the targeted area. The motivation to play the sensing game is twofold: 1) The game provides an exciting *real-world gaming experience* to the players, and 2) The players can *learn useful information about the environment* such as the WiFi coverage map which lists the locations having best WiFi signal strength near the player's location.

A. Design and Implementation

The game contains the following entities/characters:

- *CGS*: The Central Game Server (CGS) controls the sensing game environment on the mobile devices and stores the players' profiles and the collected sensing data.
- *Player*: Users who play the game on their mobile devices.
- *Alien*: A negative role character that needs to be found and destroyed by the players. Aliens are controlled by CGS according to the sensing coverage strategy.

Game story: The aliens in the game are hiding at different locations across the targeted area. Players can see the aliens on their screens only when they are close to the alien positions. This is done in order to encourage the players to walk around to discover aliens; in the process, we collect sensing data. At the same time, this makes the game more unpredictable and potentially interesting. The game periodically scans for nearby aliens and alerts the players when aliens are detected; the player locates the alien on the game screen and starts shooting at the alien using the game buttons. When an alien gets hit, there are two possible outcomes: if this is the first or second time the alien is shot, the alien escapes to a new location to hide from the player. To completely destroy the alien, the player has to find and shoot the alien three times, while hints of the alien's location are provided after it was shot. In this way, the players are provided with an incentive to cover more locations. Players are rewarded with points for shooting the aliens. All players can see the current overall player ranking.

The sensing side of the game: Sensing data is collected periodically when the game is on. The placement of aliens on the map seeks to ensure uniform sensing coverage of the area. The challenge, thus, is how to initially place and then move the aliens to ensure fast coverage while at the same time maintain a high player interest in the game.

In the initial phases of sensing, CGS moves each alien to a location which is not yet covered, but later on it moves the alien intelligently from one location to another by considering a variety of factors (e.g., less visited regions, regions close to pedestrian routes, or regions which need higher sensing accuracy). In this way, the game manages to entice users from popular regions to unpopular ones with a reasonable coverage effort. Generally, the alien will escape to farther away regions, and the players might be reluctant to follow despite the hints provided by CGS. To increase the chances that players follow the alien, we provide more points for shooting the alien for a second time, and even more for the third (fatal) shot.

Game difficulty and achievements: We designed the game with difficulty levels based on the number of killed aliens, the bullets collected from around the player's location, and the total score of the player. In this way, players have extra-incentives to cover more ground. A player has to track and kill a minimum number of aliens to unlock specific achievements and to enter the next levels in the game. We leverage the achievements APIs provided in Android platform as part of Google Play Game Services which allow the players to unlock and display achievements as shown in Figure 1 (right).

Prototype Implementation: We implemented a game prototype for Android-based smart-phones and deployed it on Google Play. An alien appears on the map when the player is close to the alien's location, as shown in Figure 1 (left). The player can target the alien and shoot it using the smart phone's touch screen. When the alien escapes to a new location, its

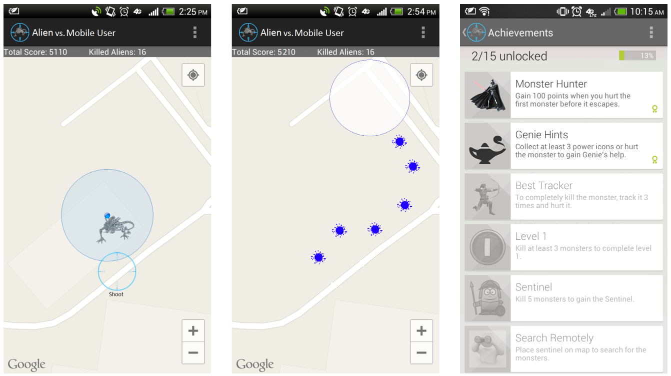

Fig. 1. Alien vs. Mobile User app: finding and shooting the alien (left); alien "blood trail" (middle); player achievements (right).

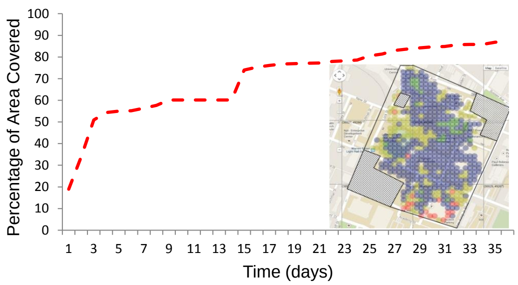

Fig. 2. Area coverage over time while performing crowdsensing with mobile gaming for the first four weeks of the user study. Illustration of the coverage overlayed on the campus map. Some areas have been removed from the map as they are not accessible to students.

"blood trail" to the new location is provided to the player as a hint to track it down (as shown in Figure 1 (middle)). The server side of the game is implemented in Java using one of the Model View Controller frameworks involving EJBs/JPA models, JSP/HTML views, and servlets, and it is deployed on the Glassfish Application Server.

B. User Study

We evaluate the benefits of gamification for crowdsensing through a user study that seeks to: (1) Evaluate the area coverage efficiency, and (2) analyze the players' activity and individual contributions to area coverage.

This study ran for 35 days, during which 53 players used their Android devices to play our game and collect WiFi data outdoors and indoors. We did not select the users in any way. To advertise the game, we placed fliers throughout the campus and sent emails to students enrolled in computing majors; users continuously registered throughout the study period.

Outdoor area coverage. Figure 2 shows the area coverage efficiency. We observe that players get highly engaged in the game from the first days, which leads to high coverage quickly (50% of the target area is covered in less than 3 days). The coverage progress slows down after the initial phase due to several reasons. First, the results show only the coverage of ground level. However, starting in the second week, aliens have also been placed at higher floors in buildings; this coverage is not captured in the figure. Second, the slowdown is expected

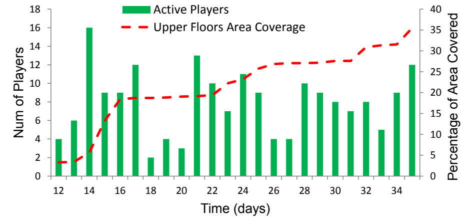

Fig. 3. Correlation of active players and the number of squares covered at different floor levels over time in last two weeks of the user study.

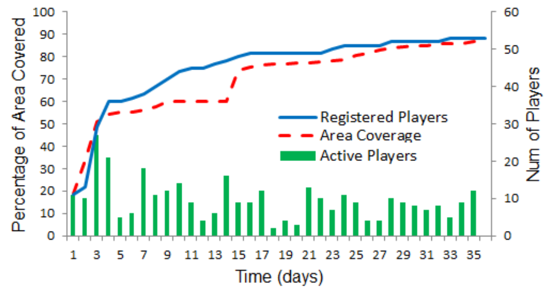

Fig. 4. Impact of the number of registered players and the number of active players on area coverage over time in the user study.

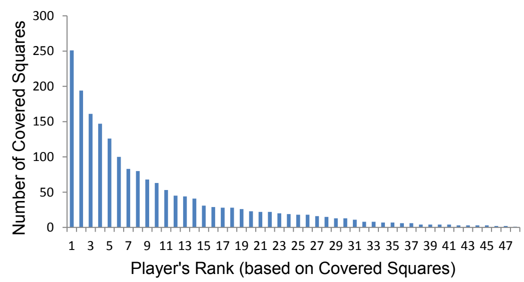

Fig. 5. Ranking players based on the number of covered squares in the area (area is divided in 10mx10m squares). 48 out of 53 players covered ground on campus.

to happen after the more common areas are covered, as the players must go farther from their usual paths. Third, we observe that the coverage remains mostly constant over the weekends as our school has a high percentage of commuters and thus mobile users are not on campus (as we see on days 4 to 6, and 11 to 13).

Figure 2 also overlays the collected WiFi data over our campus map. The color coding for the WiFi signal strength is: green for areas with strong signal; blue for areas with medium signal; yellow for areas with low signal; and red for areas with no signal. Overall, we achieve 87% area coverage of the campus in a four week period.

Indoor area coverage. Figure 3 plots the correlation of active players and the number of squares covered at upper floors over time (we started to place aliens on upper floors on day 12). Indoor localization was achieved based on WiFi triangulation and the barometric pressure sensor in the phones; we omit the details for the sake of brevity. We observe that indoor coverage correlates well with the number of active players, and the pattern is similar to outdoor coverage. Overall, the game achieved 35% coverage of the upper floors. Despite apparently being low, this result is encouraging: The players

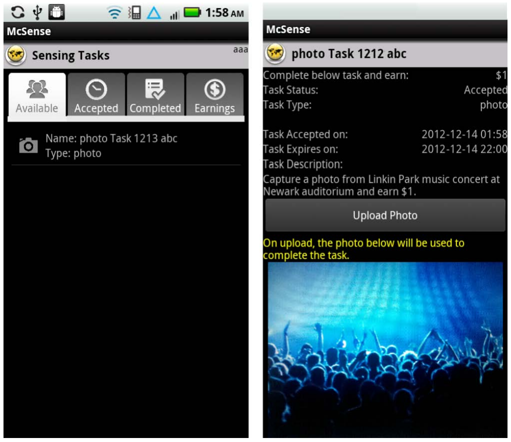

Fig. 6. McSense mobile app.

covered many hallways and open spaces in each building, but could not go into offices and other spaces that are closed to students; however, aliens were placed there as well. To avoid placing aliens in such locations and wasting players' effort, we plan to investigate a crowdsourcing approach, in which the players mark the inaccessible places while playing the game.

Player activity. Figure 4 presents the impact of the number of registered players and the number of active players on area coverage over time. The results show the improvement in area coverage with the increase in the number of registered players in the game. This proves that the players are interested in the game and are involved in tracking the aliens. The players are consistently active in the week days over the period of the study, and they are less active in the weekends. For additional insights on the individual contribution of the players, Figure 5 presents the players' ranks based on number of covered squares in the area. We observe a power-law distribution of the players' contribution to the area coverage.

IV. McSense: Crowdsensing Based on Micro-Payments

We have designed and implemented McSense [3], a mobile crowdsensing platform based on micro-payments that allows clients to collect many types of sensing data from phones.

A. Design and Implementation

The architecture of McSense has two main components: (1) the server platform that accepts tasks from clients who want to collect sensing data and makes individual tasks available for execution on smart phones belonging to registered users, called providers; and (2) the mobile application that accepts individual tasks from the server, performs sensing, and submits the sensed data to the server.

The McSense application, shown in Figure 6, has been implemented in Android and is compatible with smart phones running Android OS 2.2 or higher. The Android application was deployed to Google Play. The server side of McSense is implemented in Java using one of the Model View Controller frameworks. The Derby database is used to store the registered user accounts and assigned task details. The server side Java code is deployed on the Glassfish Application Server.

New sensing tasks can be posted by clients using a web interface running on the McSense server. Once a new task is posted, a background notification service running on the phone identifies the new available tasks and notifies the provider with a vibration. When the application is loaded, the providers can see four tabs (Available, Accepted, Completed and Earnings) as shown in Figure 6. When a provider selects an available task (i.e., views the task details and the associated micro-payment) and clicks on the Accept button, the task is moved to the Accepted tab. When the accepted task is completed according to its requirements, the task is moved to the Completed tasks tab. Finally, the providers view their aggregated total earnings for successfully completed tasks under the Earnings tab.

Two types of tasks were made available to users in McSense: *manual*, which require user's input; and *automatic* which runs in the background on the phone without user's intervention. All the automated tasks were daily tasks, and the users had to provide data for at least 6 hours. Specifically, the users chose from the following list of tasks:

Manual Photo Sensing Task: Registered users are asked to take photos from specific events on campus. These photos could be used by the university news department for current news articles.

Automated Sensing Task Using Accelerometer and GPS: The accelerometer and GPS readings are collected at 1 min intervals. These readings are stored on the phone and uploaded to the McSense server on task completion. These data could be used for personal analytics such as discovering user activities.

Automated Sensing Task Using Bluetooth: The user's phone performs periodic Bluetooth scans (every 5 min) and stores the data about the discovered Bluetooth devices locally. On task completion, the data is uploaded to the McSense server. These data can provide social information such as user co-presence which could be used to quantify the level of "physical" social interactions.

Automated Resources Usage Sensing Task: The usage of user's phone resources is sensed and reported back to the McSense server. Specifically, the report contains the network usage, periodic WiFi scans, the battery level, and the applications' usage (including per-application network usage).

B. User Study

We evaluated the effectiveness of micro-payments in crowdsensing through a user study that seeks to understand: (1) the efficiency of area coverage, (2) the reliability of user provided data, and (3) the relation between monetary incentives and task completion.

This study ran for 2 months with 50 students, who volunteered and registered at the beginning of the study. The photo tasks which require more effort from participants are paid $10, $5 and $3 per task. The photo tasks which require less effort by participants are paid $2, $1, and 50 cents per task. The automated sensing tasks require less effort by participants and are paid between 50 cents and $2 per task.

Area Coverage. To make the results as consistent as possible with the results from the gaming approach, we

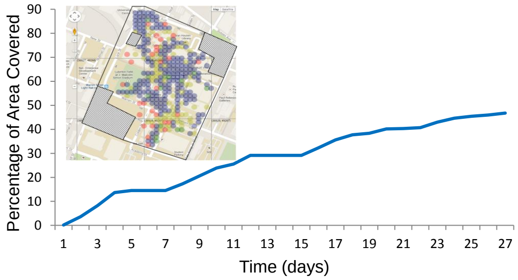

Fig. 7. Area coverage over time while performing crowdsensing with micro-payments. Illustration of the coverage overlayed on the campus map. Some areas have been removed from the map as they are not accessible to students.

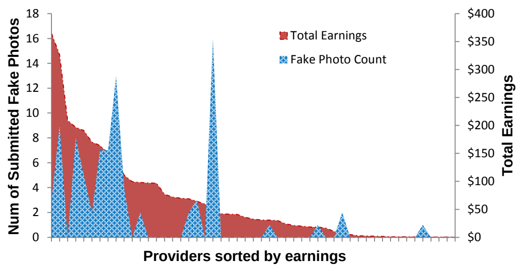

Fig. 8. Relation between user earnings and number of fake photos.

investigate the coverage based on the collected WiFi data. These data were collected as part of the *resource usage task* and happened in the last 28 days of the study. During this study, there were always resource usage tasks available to users. Furthermore, the users were directed to various regions on campus by other tasks (e.g., taking photos from certain events), thus improving the sensing coverage. Specifically, this method allows us to capture additional indoor WiFi data from places where users do not typically go. For example, the participants were asked to capture photos of recycle bins at each floor in the campus buildings along with room numbers. The system administrator made sure there were always photo tasks available for the participants on each day of the user study (including weekends).

Figure 7 shows the area coverage efficiency of the micro-payments approach. The WiFi signal strength data is plotted with the same color coding as in the gaming study. We observe a relatively constant increase in the coverage over time in the first 3 weeks, especially during week days. Toward the end of the study, the rate of coverage decreases as most of the common areas have been covered. We speculate that users did not find the price of the tasks enticing enough to go to areas located far away from their daily routine. Overall, the micro-payment approach achieves 46% area coverage of the campus in the four week time period.

Reliability of User Provided Data. The results in Figure 8 prove that sensed data submitted by the participants is not always reliable. To determine the fake photos, we manually validated all the collected photos. The results also demonstrate that the users who submitted most of the fake photos are among the top 20 high earners. At the same time, we observe that these malicious users have also submitted good photos at a very high rate compared to the fake photos. As such, we conclude that the malicious users are not a significant menace, but may cause some confusion in the collected data. Therefore, it may not be a good idea to remove the malicious users from the system as soon as they are caught cheating; instead, the fake data should be filtered out when detected.

V. Discussion and Lessons Learned

This section presents a few lessons learned from the field studies and discusses future challenges and possible improvements based on these insights.

A. *Sensing Task Duration*

The duration of a task plays an important role in determining whether gaming or micro-payments would be more suitable for a crowdsensing campaign. For the gaming approach to be efficient, it is extremely important that the game design includes strong in-game incentives such that the players remain engaged over time. The stronger the in-game incentives are, the longer the gaming approach remains effective. From our user studies, we can conclude that for medium-term sensing efforts both gaming and micro-payments approaches could be effective (the two studies ran for a comparable amount of time).

However, for much longer sensing efforts (e.g., 1 year), we speculate that micro-payments would be more effective because monetary incentives do not depreciate, whereas in-game incentives might not be sustainable over such long periods. Similarly, we expect the micro-payments to perform better for tasks with tight time constraints such as taking a photo from a given event. In our study, the participants were willing to take a photo at a particular location during a particular time of the day for a reasonable micro-payment. In this regard, the gaming approach might not be as effective in quickly luring away players from their current path/activity.

B. *Sensing Task Type*

We realize that there is no “one-size fits all” solution for all types of crowdsensing [15]. Consider the following two types of crowdsensing: 1) uniform area coverage sensing, and 2) participant activity sensing. From our observations, the gaming solution works well for area coverage sensing. However, it may not be the right fit for participant activity sensing because gaming would lead to changes in participant activities, and thus will not capture the desired sensing data of the participant. Instead, the micro-payments based solution will be more suitable to capture the expected personal analytics.

In our mobile game study, the focus was mainly on automatically collecting sensing data, where players are not annoyed with any manual sensing tasks. In principle, micro-payments are a better fit for manual sensing. However, mobile games can also be used for this type of sensing if the sensing task does not have tight time constraints and its requirement can be translated into a game action. For example, a player could receive an in-game request to take a photo of the location where a game character was destroyed.

C. Incentive Quality or Value

The amount of collected crowdsensing data and the quality of the area coverage, where required, depend strongly on the incentive quality or value. To understand the effectiveness of our in-game incentives, we collected game feedback from the players at the end of the study by asking them "What made you to continue playing the Alien vs. Mobile User game"? We received answers from 16 players. The responses show that the majority of the players were curious about the game story and they liked tracking the aliens hiding in the campus buildings. Other primary reasons for playing were: moving to the next game levels and being on top of the leaderboard, competing with friends, winning game achievements, and checking the game graphics. Furthermore, we analyzed various game variables, such as the number of players who unlocked the achievements and the mean time to unlock achievements and complete each game level, to understand the player engagement in the game. The results, omitted here, demonstrated that the game levels and achievements worked reasonably well; they were challenging enough and sustained players' interest during the study.

In the micro-payments study, the average price of the posted task was \$1.18 and the average price of the completed task was \$0.84. To observe the impact of price on task completion, we posted a few tasks with a higher price (\$2 - \$10). We noticed a 15% increase in task completion success rate for these tasks compared with the rest of the tasks. In addition, we noticed an improvement in data quality for the high priced photo tasks, with clear and focused photos compared to the low priced photo tasks (i.e., the tasks priced \$1 or lower). Thus, our study confirms that task pricing influences the data quality. However, it is not clear whether further increase in the task price may address the issue of uniform area coverage in a cost effective manner. On the other hand, as demonstrated by our gaming study, in-game incentives proved to be a cost effective solution for area coverage.

D. Sensing Data Reliability

As emphasized by the results of our micro-payment study, data reliability could be a significant problem in crowdsensing. The analysis of our results indicate a high correlation between the amount of time spent by users out of campus and the number of fake photos they submitted. This observation suggests that a first step toward ensuring data reliability is to incorporate location authentication mechanisms in crowdsensing. This solution applies independent of the type of incentives. In the absence of such a mechanism, statistical analysis of user's mobility traces, if available, could provide hints on which data points should be inspected critically (i.e., those from places infrequently visited by the user). Mobility traces could be more available for the gaming approach, as the games are expected to be designed to adapt to the user's location.

E. Mobile Resource Consumption

The sensing tasks should consume little resources, especially battery and cellular data, on the smart phones if crowdsensing is to be successful. For example, games should offload computationally-expensive tasks to the servers/cloud. Since cellular data consumption can lead to overcharges, an option is to give players the ability to control the frequency of game status updates when using cellular data, thus choosing the desired trade-off between game accuracy and saving the phone's resources.

Similarly, long running micro-payment tasks such as daily accelerometer and location data collection for activity recognition should be designed to ensure the phones do not run out of battery due to these tasks. The results from our micro-payment study showed that some users decided to abort the tasks when the power dropped under a certain level. However, we also observed that many users were recharging their phones during the day, presumably to complete the tasks and receive the monetary incentive. Existing research on continuous sensing on the phones seems promising, and once widely deployed it will alleviate such issues.

F. How General Are Our Insights?

The results of our user studies provide us with valuable information about the effectiveness of crowdsensing based on gaming and based on micro-payments for a medium size urban university campus: an area of 1600 x 1200 feet with buildings between 4-6 floors, and student participants mostly between 18-22 years old. One can imagine a variety of crowdsensing efforts that target similar settings and our findings would hold in those settings. Besides university campuses, business districts or even urban neighborhoods with many young and technology-savvy professionals could achieve similar results. In addition, not every social category and age group has to be represented for certain sensing tasks such as mapping a region with sensor readings. For example, uniform area coverage is not expected to be strongly dependent on the demographics of the participants and does not require a very large number of players in the gaming approach. Our results showed that a relatively small number of passionate players quickly covered a large region.

Ideally, a wider exploration of different alternative designs of the experiments would have provided additional insights. For example, one could imagine a scenario in which each user is asked to perform data collection tasks based on micro-payments and to play the game alternatively during the duration of the study. This was not feasible given the resources available for the project. Finally, for other types of sensing tasks, such as collecting personal analytics data, the results may vary as a function of the area size as well as the population type and size.

VI. Conclusions

Crowdsensing has the potential to collect large amounts of data from the physical world if the right incentives are employed for each type of sensing task. Before choosing a particular incentive, the designers of crowdsensing systems need to consider the trade-offs among the type of sensing, the desired spatio-temporal properties of the data, the level of data reliability required, the monetary cost, the user effort, the user privacy, and the resource consumption on mobile devices. A worthy endeavor moving forward is to build systems that consider all these factors and guide the designers or users of crowdsensing systems on choosing an appropriate incentive for a particular situation.

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