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Road Pavement Condition Monitoring by Embedded Crowdsensing

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16. Abstract

This project investigates the design, implementation, and testing of a crowdsensing-based system that allows for pavement condition monitoring in a low-cost, reliable, and rapid manner. It also studies the incentive mechanisms for pavement crowdsensing that properly stimulate users to complete sensing tasks within the budget of platform cost and overall completion time. We have tested the pavement crowdsensing system with the goal to ensure that it conforms to functional and nonfunctional requirements. We have designed a platform-driven greedy algorithm with nine incentive mechanisms and evaluated their performance; our methods can avoid the cost explosion problem observed in data-reverse-auction incentive mechanisms, and the best of them can reduce the overall completion time by half compared to task-reverse-auction incentive mechanisms. Additional simulations and experiments are recommended to be carried out in the future to study the performance of the pavement crowdsensing system and associated incentive mechanisms in large-scale deployment.

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CHAPTER 1

Introduction

BACKGROUND

Modern methods for road pavement condition monitoring take advantage of new technologies in precision instrumentation to realize automatic measurements [1]. For example, the laser crack measurement systems (LCMS) use high-speed cameras, custom optics, and laser line projectors to acquire 2D images and high-resolution 3D profiles of road surfaces [2]. However these present pavement-monitoring procedures are time consuming and costly [3], which limits their abilities to scale in frequency and coverage. Recently the U.S. Department of Transportation (DOT) has initiated a Connected Vehicle Program, which promotes applying vehicle-to-X (V2X) data to pavement monitoring. A study by the Center for Automotive Research and administered by Michigan DOT [4] reports that using V2X data for pavement monitoring is possible but it will require novel and proactive techniques of data use and management. The state-of-the-art research in this domain employs embedded crowdsensing via mobile phones to provide a low-cost approach to pervasive-coverage sensing. However, it presents a couple of unsolved issues along with technical and social challenges including sensing accuracy, the fidelity of mobile sensing results, and incentive schemes for crowdsensing participation.

OBJECTIVE

The objective of this project was to design, implement, and test a crowdsensing-based system that allows for pavement condition monitoring in a low-cost, reliable, and rapid manner.

POTENTIAL FOR IMPACTING THE STATE OF PRACTICE

The success of this project will impact the state of practice by providing an alternative approach to pavement monitoring and decision making, which will have advantages over existing practices in monitoring costs, frequency, and coverage.

CHAPTER 2

Methodology

INTRODUCTION

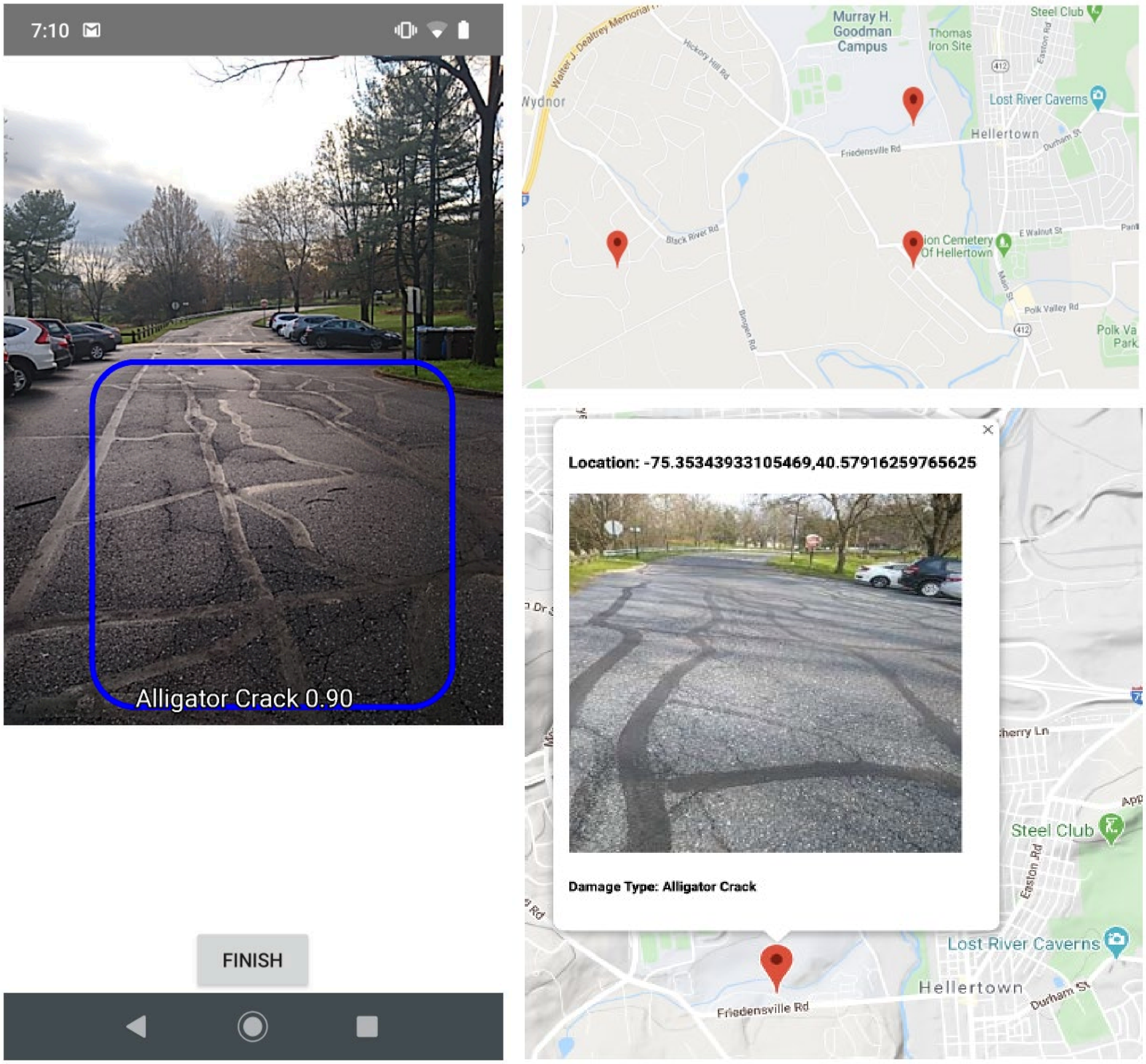
This project was carried out in two thrusts of work: (1) computer-vision based pavement distress crowdsensing and (2) incentive mechanisms for pavement crowdsensing. In the first thrust, we have developed a crowdsensing system with a mobile application that supports road damage detection using deep neural networks with images captured through a smartphone. The code repository is available at https://github.com/LONGLAB-projects/mobile-pavement-monitoring. In the second thrust, we have evaluated nine incentive mechanisms through simulations in terms of their platform costs and total operation times. Our results provide guidance in selecting the best incentive mechanism in different settings of pavement crowdsensing [5].

COMPUTER-VISION BASED PAVEMENT DISTRESS CROWDSENSING

The pavement crowdsensing system consists of three components: a mobile application as the front end interacting with crowdsensing participants, the backend including a database, and a dashboard for DOT-related personnel to visualize the crowdsensing results.

We have designed and implemented the mobile application on the Android platform. It uses a state-of-the-art machine learning model for detecting pavement damage based on images captured by the Android-phone camera and classifying them into eight types with corresponding confidence [6]. The types include (1) liner crack, longitudinal, wheel mark part; (2) liner crack, longitudinal, construction joint part; (3) liner crack, lateral, equal interval; (4) liner crack, lateral, construction joint part; (5) alligator crack; (6) rutting, bump, pothole, separation; (7) white line blur; and (8) crosswalk blur. We have chosen this machine learning model because it "achieved recalls and precisions greater than 75% with an inference time of 1.5 s on a smartphone."[6] Here the recall is defined as the number of true positives divided by the number of true positives plus the number of false negatives, and the precision is defined as the number of true positives divided by the number of true positives plus the number of false positives.

Once the confidence level associated with a pavement damage type is higher than a threshold (e.g., 60%) the mobile application will collect the latitude and longitude information of the current location, the image, and the confidence from the smartphone, and send them to the backend server (Figure 1a). When the backend server receives the data, it will verify the data and generate a certificate for them. With the certificate, the data can be saved in a real-time database. When the DOT-related personnel opens the dashboard web page, all stored data will be rendered on a Google Map as markers (Figure 1b).



(a) (b)

Figure 1. (a) User interface of the mobile application; (b) user interface of the dashboard.

Android Application

The application has been developed in Android Studio. It starts with a homepage that supports three buttons corresponding to “Drive & Detect,” “Contact Us,” and “Privacy Policy.” Clicking the “Drive & Detect” button leads to a Detection page: If the image captured by the smartphone camera contains pavement damage, the object detection model based on convolutional neural networks [6] will delimit a bounding box and generate the corresponding confidence and damage type. At the bottom of the Detection page, there is a button which the user can click to go back to the homepage when they want to end the detection. The application also provides “Contact Us” and “Privacy Policy” pages for users to submit feedback and read policy information.

Database in the Backend

We chose Firebase, a cloud-hosted realtime NoSQL database, to store all data in the backend. The data structure in the Firebase database is like a JSON (JavaScript Object Notation) tree and all data are stored in the database in the form of key-value pairs. There are two collections in the database: one is used to store the feedback from users and the other is used to store the data about pavement distresses. Figure 2 depicts a snippet of the data structure recording the pavement distress information.

Figure 2. Data structure used to represent pavement distress data in Firebase.

Dashboard

The project aims to help the Department of Transportation to monitor road pavement conditions in a low-cost way. It is important to provide a visualization of the pavement distresses detected to DOT-related personnel to help them decide pavement maintenance and repair needs. Our system has a dashboard that offers an overview of all the saved data in Firebase. It marks all positions on a Google map as red and when one clicks on a marker, it will display the pavement distress information at the corresponding location, which includes the precise location data, the image of the road pavement condition, and the pavement distress type as shown in Figure 1b.

INCENTIVE MECHANISMS FOR PAVEMENT CROWDSENSING

During the 99th Transportation Research Board Annual Meeting held in Washington, DC on Jan. 14, 2020, we demonstrated our first version of the pavement crowdsensing system [7] to visitors to our booth and DOT members, including then Deputy Assistant Secretary for Research and Technology. An important question that had been discussed during our demo was how incentive mechanisms would impact the performance of pavement crowdsensing. In fact, how to properly motivate users to participate in crowdsensing tasks with a low platform cost remains an open question.

In our research, we modeled the pavement crowdsensing problem and designed new incentive mechanisms based on a platform-driven greedy algorithm. The rewards of sensing tasks are determined by the specific incentive mechanisms. With this algorithm, the user selects the sensing task that can provide the highest net profit margin. These incentive mechanisms are evaluated and compared in different scenarios in terms of the platform cost and the overall task completion time through extensive simulations. Our methods can avoid the cost explosion problem observed in data-reverse-auction incentive mechanisms, and the best of them can reduce the overall completion time by half compared to task-reverse-auction incentive mechanisms.

Research Problem and its Model

For our research problem, the platform (i.e., the pavement crowdsensing system) needs pavement condition data in certain areas. Thus, we need to motivate the users using the platform to collect the data. In this case, our research objective was to design an appropriate incentive mechanism to help the platform achieve an area coverage target with a low cost and total operation time. Based on the comparison results of incentive mechanisms, the platform can choose the best incentive mechanism with the lowest budget for different area coverage targets.

Our model of the research problem contains three entities: the area, the sensing task, and the user. Each entity can be described by its behavior and/or its relationship with other entities:

1. The area entity is modeled according to the Manhattan model as a grid of cells without loss of generality for incentive mechanism studies. The grid has a uniform distribution of cost for traveling across adjacent cells, and no missing cells within. The area represents the types of roads that users may encounter and the varying costs of traveling with different pavement conditions. Meanwhile, the area has another constraint for users. Users can only move horizontally or vertically in one step at a time.

2. The sensing task entity contains information on the location of interest and the monetary incentive associated with user participation. The sensing tasks specify roads where pavement sensing is needed.

3. The user entity represents users participating in the crowdsensing. As users continue to participate and collect and report data for rewards, they accumulate monetary rewards and incur operation costs.

Incentive Mechanisms

We have designed a platform-driven greedy algorithm that selects an available task that gives the maximum profit to the user. The maximum profit is impacted by the incentive mechanism. After this algorithm finds out the task, which can provide the maximum profit for a user, the user needs to check whether the net profit margin of the task is greater than a threshold. If positive, the user selects the task; otherwise, the user drops out.

We studied nine incentive mechanisms: (1) Task-Reverse Auction, (2) Static Uniform (SU), (3) Dynamic Relative (DR), (4) Dynamic User Centric (DUC), (5) Static User Centric (SUC), (6) Dynamic Task Centric (DTC), (7) Static Task Centric (STC), (8) Dynamic Pit (DPIT), and (9) Static Pit (SPIT) incentive mechanisms. Their mathematical formulas are described in Appendix I.

Evaluation Metrics

The purpose of the evaluation metrics is to offer a means of differentiating the incentive mechanisms and to guide the design of the crowdsensing solutions. The simulations for incentive mechanism evaluations consist of an extensive number of trials. In each trial, we initialize the tasks and users at the beginning and the simulation runs until all tasks are completed or all users drop out. The details of the evaluation metrics are described as follows.

1. The total operation time *tf* represents the duration of a trial. In one trial, a timer starts from time 0 and ends at the time *tf* when all sensing tasks are completed or all users drop out. While two incentive mechanisms may have an equal success rate *sr*, one incentive mechanism might have less total operation time *tf*. This implies that users have been incentivized to select and perform tasks in efficient ways.

2. The platform cost is the amount of money that the platform pays the users through sensing task rewards. The surplus is the portion of the budget that is not used by the end of a trial. A lower platform cost reflects the ability of incentive mechanisms to reduce the cost for sensing task rewards.

CHAPTER 3

Findings

COMPUTER-VISION BASED PAVEMENT DISTRESS CROWDSENSING

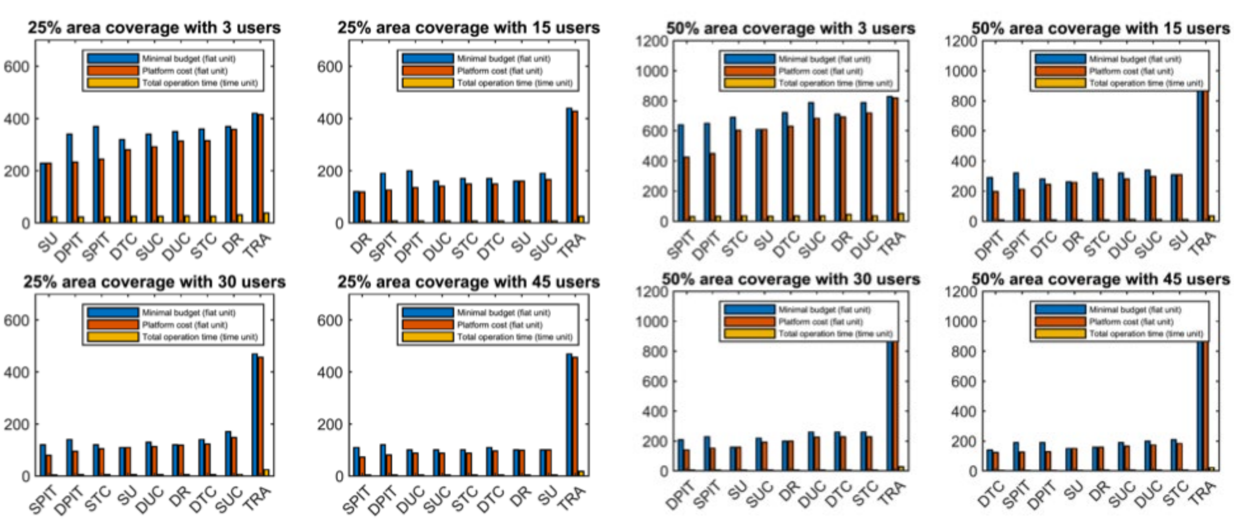
System Evaluation

We have tested the pavement crowdsensing system with the goal to ensure that the AUT (application under testing) conforms to functional and nonfunctional requirements and makes sure that all bugs or issues are identified and fixed before going live. We have identified which functional or nonfunctional requirements would be tested, including (1) whether the application can run without a crash; (2) when there is suspected road damage (the confidence level is higher than the threshold), whether the database can receive related data or not; and (3) whether the dashboard can get all data from the database and render them on a Google Map or not. Integration testing was conducted to evaluate the system with respect to the above-mentioned three aspects and the system passed the test. The crowdsensing-based system developed enables pavement condition monitoring in a low-cost, reliable, and rapid manner.

INCENTIVE MECHANISMS FOR PAVEMENT CROWDSENSING

Incentive Mechanism Comparison

Incentive mechanisms were evaluated and compared in three scenarios corresponding to low, medium, and high area coverage percentages for pavement crowdsensing with different numbers of users.



(a) (b)

Figure 3. Incentive mechanism comparison: (a) 25% area coverage and (b) 50% area coverage.

The platform cost is used to order the incentive mechanisms based on their performance data as shown in Figure 3. The minimal budgets shown in Figure 3 are the lowest budgets that can realize a 100% success rate for the targeted area coverage percentage. This means that any budgets higher than this value allow the platform to achieve the 100% success rate for the targeted area coverage.

Given 25% area coverage, Figure 3a shows that the SU and DR incentive mechanisms respectively have the lowest platform costs when the platform has 3 users and 15 users. Apart from this, the static and dynamic pit incentive mechanisms always rank among the top three incentive mechanisms in all scenarios. Given 50% area coverage, Figure 3b shows that static and dynamic pit incentive mechanisms still have the best performances of the platform cost in all scenarios. Even though the DTC incentive mechanism achieved the lowest platform cost in 50% area coverage with 45 users, this observation does not conflict with the previous statement. Figure 3 in Appendix I depicts the results corresponding to 75% area coverage, which confirms that SPIT and DPIT always have the lowest platform cost regardless of how many users the platform has. Based on the observations described above, we conclude that SPIT and DPIT are two incentive mechanisms among the ones evaluated that have the lowest platform cost.

Our design of incentive mechanism can avoid the cost explosion problem observed in data-reverse-auction incentive mechanisms, and the best of them can reduce the overall completion time by half compared to task-reverse-auction incentive mechanisms. Details are described in Appendix I of this report.

CHAPTER 4

Recommendations

COMPUTER-VISION BASED PAVEMENT DISTRESS CROWDSENSING

Large-scale Deployment and Evaluations

We have successfully designed, developed, and tested the pavement crowdsensing system. Due to the time limitation and the pandemic situation, we have not been able to conduct large-scale deployment and evaluations of the system. Thus we recommend recruiting volunteers on a large scale and conducting evaluations of the system in terms of its scalability and performance in the future.

Security of the Crowdsensing System

The pavement crowdsensing system supports secure communication between front-end mobile application and the backend server. However, it is possible that malicious users may initiate attacks to the system by providing fake data, such as a fake image for a certain location. A potential solution is to use machine learning to address this issue so that consensus among the crowd will help mitigate the impact by the fake data provided by malicious attackers. We recommend studying approaches that enhance the security of the crowdsensing system in the future.

Pavement Distress Indicator Development

The pavement crowdsensing system can detect pavement distress conditions and categorize them into eight existing categories. DOT-related personnel can use the dashboard to check the images and data to decide pavement maintenance and repairement needs. It should be helpful if indicators could be developed (e.g., image-based distress indictors and accelerometer-based roughness indictors for existing pavement conditions) based on the crowdsensing data and their correlations with conventional IRI (International Roughness Index) and PCI (Pavement Condition Index) could be established for decision making.

INCENTIVE MECHANISMS FOR PAVEMENT CROWDSENSING

Large-scale Simulations and Experiments

We have identified a couple of incentive mechanisms for crowdsensing based on our incentive mechanism design that properly stimulate users to work for the platform and bound/reduce platform cost and overall completion time of the sensing tasks. We recommend that large-scale simulations and real-life experiments through integrating the incentive mechanisms in our pavement crowdsensing system should be conducted in the future.

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APPENDIX I

Incentive Mechanisms for Pavement Crowdsensing with a Platform-driven Greedy Algorithm

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Abstract

Crowdsensing nowadays is regarded as an effective method to collect specific data due to its pervasiveness and convenience. There are projects using crowdsensing to collect pavement condition data. However, how to properly motivate users to participate in crowdsensing tasks with a low platform cost remains an open question. In our research, we model the pavement crowdsensing problem and design new incentive mechanisms based on a platform-driven greedy algorithm. The rewards of sensing tasks are determined by the specific incentive mechanisms. With this algorithm, the user selects the sensing task that can provide the highest net profit margin. These incentive mechanisms are evaluated and compared in different scenarios in terms of the platform cost and the overall task completion time through extensive simulations. Our methods can avoid the cost explosion problem observed in data-reverse-auction incentive mechanisms, and the best of them can reduce the overall completion time by half compared to task-reverse-auction incentive mechanisms.

Keywords: crowdsensing, pavement monitoring, monetary incentive, incentive mechanism

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1 Introduction

As road infrastructure continues to increase in size and complexity, new and innovative solutions must be developed to cope with road degradation. Current methods used to collect road condition information do not mitigate the stress in covering 4.18 million miles of road in the U.S [1]. One viable solution is to create a crowdsensing platform for smartphone users to collect road pavement data. For example, detecting and reporting poor road conditions by using embedded cameras, accelerometers, and 4G/5G networks. To support such a network, an active user base must be established and maintained. Users' participation is at the heart of creating diverse data pools and addressing quality road condition information. The component needed to satiate users' drive, and to generate the aforementioned benefits, is described as the incentive mechanism.

As we want to motivate more people to participate in performing the sensing tasks, an appropriate incentive mechanism allows the platform to properly stimulate the users to work for the platform and bound/reduce *platform cost* and *overall completion time* of the sensing tasks, which is also called *total operation time* in this report.

In our research, the platform wants to economically collect pavement condition data for a certain target area. In this report, we introduce a set of incentive mechanisms and study how pavement crowdsensing may cover a target area with the lowest platform cost and the smallest total operation time. The incentive mechanisms we design are based on a platform-driven greedy algorithm, which motivates users to select sensing tasks that can provide the highest net profit margin. Each incentive mechanism has a unique reward generation formula, which is designed within the context of road coverage. We have evaluated 9 incentive mechanisms through simulations in terms of their platform costs and total operation times. Our results provide guidance in selecting the best incentive mechanism in different settings of pavement crowdsensing.

Here are the key contributions of our research:

- The incentive mechanisms we design can effectively avoid the cost explosion problem as users choose their sensing tasks before starting to work on them so that a sensing task can only be done by no more than one user.

- Our incentive mechanism enables users to select sensing tasks that offer the highest net profit margin based on a greedy algorithm.

- The total operation time or the overall completion time of our approach is reduced comparing to that of the task-reverse-auction incentive mechanism. Our research helps the pavement crowdsensing platform to find a solution to crowd-sense the target area within a limited budget.

The rest of the report is organized as follows. We first survey the related work in Section II. Then we introduce the research problem and its model in Section III and present our incentive mechanism solutions in Section IV. Section V describes how we construct simulations for evaluating the incentive mechanisms. Section VI shows and discusses the evaluation results and Section VII concludes this report.

2 Related Work

2.1 Existing monetary incentive mechanisms

Zhang [14] and Jamies [11] both assort incentive mechanisms by the types of incentives. In Jamies [11], monetary and non-monetary incentives are compared. Non-monetary incentive mechanisms [2, 3] rely on the continued participation of users due to intrinsic motivations. Monetary incentive mechanisms [4–10, 15, 16] rely on the direct backing of fiat money or indirect backing of fiat money through alternative currencies. As a result, using non-monetary incentives cannot assure that enough users participate in sensing tasks. According to a survey paper [14], monetary incentives will be more likely to motivate users to complete the sensing tasks. Therefore, a monetary incentive mechanism is more fitting for crowdsensing and will be considered in our research. However, some monetary incentive mechanisms [5,10] have different shortages such as a cost explosion problem [14] while others may not fit in our research scenarios because they target at achieving optimal data quality [6, 10] and fairness [11]. Here are some brief descriptions of three monetary incentive mechanisms.

- For task-reverse-auction incentive mechanisms [15–17], they use a task-reverse-auction format to design their incentive mechanisms. The users would bid on the tasks posted by the platform. Then, the user who bids the lowest price can get the opportunity to perform the sensing task.

- For data-reverse-auction incentive mechanisms [4, 10], they use a data-reverse-auction format to design incentive mechanisms. In the auction process, users offer their sensing data of tasks and their prices to the platform. Then the platform would select the data that satisfies its requirement and pay for the price.

- In the platform-centric model [6], it treats the crowdsensing problem as a Stackelberg game. By changing the reward of the task, both users and the platform would reach a Nash equilibrium.

2.2 Comparison with three types of incentive mechanisms

Most of the existing incentive mechanisms are designed by auction theory and game theory. In this subsection, we compare our incentive mechanisms with three existing types of incentive mechanisms.

For the task-reverse-auction incentive mechanisms [15–17], their auction style cannot guarantee that the platform selects the nearby users to complete the sensing tasks because of untruthful bids [16]. In this situation, the user who is far away from a sensing task can win the auction. Further distances result in a longer travel time for users. Thus, the task-reverse-auction incentive mechanisms need more time to complete all the sensing tasks than our incentive mechanisms.

For data-reverse-auction incentive mechanisms [4, 10], while multiple users collect the data for one sensing task, only one user's data can be accepted by the platform. In other words, other users' data is wasted. As a result, this type of incentive mechanisms increase costs for car fuel, personal free time, and etc. For our incentive mechanisms, users can select the sensing task before they go to collect the data. Thus, the cost explosion problem can be avoided.

The platform-centric model [6] assumes that the platform has an unlimited budget. Therefore, it can find an optimal solution to get the highest-quality data available to the platform. Nevertheless, this incentive mechanism still has its limitations that the platform usually has a limited budget in practice use, which can be perfectly solved by our incentive mechanism.

3 Research Problem and Its Model

For our research problem, the platform needs data of pavement conditions in certain areas. Thus, we should motivate the users using the platform to collect the data. In this case, our research objective is to design an appropriate incentive mechanism to help the platform achieve an area coverage target with a low cost and total operation time. Based on the comparison results of incentive mechanisms, the platform can choose the best incentive mechanism with the lowest budget for different area coverage targets.

Our model of the research problem contains three entities: the area, the sensing task, and the user. Each entity can be described by its behavior and/or its relationship with other entities:

- The area entity is modeled according to the Manhattan model as a grid of cells without loss of generality for incentive mechanism studies. The grid has a uniform distribution of cost for traveling across adjacent cells, and no missing cells within. The area represents the types of roads that users may encounter and the varying costs of traveling with different pavement conditions. Meanwhile, the area has another constraint for users. Users can only move horizontally or vertically in one step at a time.

- The sensing task entity contains information on the location of interest and the monetary incentive associated with user participation. The sensing tasks specify roads where pavement sensing is needed.

- The user entity represents users participating in the crowdsensing. As users continue to participate and collect and report data for rewards, they accumulate monetary rewards and endure operation costs.

4 Incentive Mechanism Solutions

Modularity and scalability are critical features needed in designing a crowdsensing framework for deploying and testing incentive mechanisms. Without these features, it would be difficult to swap incentive mechanisms and evaluate them. Our crowdsensing platform and incentive mechanism designs are guided by evaluation metrics described in this section.

4.1 Notations

The symbols we use in this report are shown in Table 1. Two important variables in our model are s_j and u_i. They represent identification numbers of the sensing tasks and users. The tasks s_j and the users u_i respectively have attributes $< u_i, R_{ij}, x_j, y_j >$ and $< s_j, a_i, C_{ij}, x_i, y_i >$. For users, if s_j is 0 or -1, then the user is currently not participating because the user has not selected a sensing task or has dropped out. For sensing tasks, if u_i is 0 then the sensing task has not been assigned to a user. In addition, if a sensing task has a reward equal to 0 then its reward has been claimed.

Table 1: Common Symbols

Symbols	**Meanings**
a_i	Accumulated reward of user u_i
Avg_j	Average distance from task s_j to all users
B	Budget for the platform
BR	Base reward
b	The side length of the grid
C_{ij}	The travel cost for user u_i to complete task s_j
CR	The reward of the task that offers MP
$d_{j,uc}$	Distance from s_j to uc
$d_{j,tc}$	Distance from s_j to tc
IM	Incentive mechanism
k_i	The ranking number for u_i
MP	Maximum profit for user u_i
NPM	Net profit margin
P	Area coverage percentage
P_{ij}	Profit for u_i of sensing task s_j
PC	The platform cost
R_{ij}	Reward of the sensing task s_j for user u_i
(S) s_j	(Set of) Sensing task/ID
S_a	The set of available tasks
SID	The index of task selected by user u_i
s_r	The percentage of trials succeed
T	Threshold for net profit margin
tc	The center of locations of sensing tasks
t_f	Total operation time
(U) u_i	(Set of) User/ID
uc	The center of locations of users
x_i	x-coordinate
y_i	y-coordinate

4.2 Evaluation metrics

The purpose of the evaluation metrics is to offer a means of differentiating the incentive mechanisms and to guide the design of the crowdsensing solutions. The simulations for incentive mechanism evaluations consist of an extensive number of trials. In each trial, we initialize the tasks and users at the beginning and the simulation runs until all tasks are completed or all users drop out. The details of the evaluation metrics are described as follows:

- The total operation time t_f represents the duration of a trial. In one trial, a timer starts from time 0 and ends at the time t_f when all sensing tasks are completed or all users drop out. While two incentive mechanisms may have an equal success rate s_r, one incentive mechanism might have less total operation time t_f. This implies that users have been incentivized to select and perform tasks in efficient ways.

- The platform cost (1) is the amount of money that the platform pays the users through sensing task rewards. The *surplus* is the portion of the budget that is not used by the end of a trial. A lower platform cost reflects the ability of incentive mechanisms to reduce the cost for sensing task rewards.

$$PC = B - surplus. \tag{1}$$

4.3 Platform-driven greedy algorithm

The platform-driven greedy algorithm that we use to design our incentive mechanisms is shown in Algorithm 1. The idea of this algorithm is to select an available task that gives the maximum profit to the user. Thus, this platform-driven greedy algorithm computes the profit of task s_j to user u_i by (2).

$$P_{ij} = R_{ij} - C_{ij} \tag{2}$$

in which R_{ij} is determined by the incentive mechanisms. We will describe more details of R_{ij} in the next subsection. After this algorithm finds out the task s_i which can provide the maximum profit for user u_i, the user u_i needs to check if the net profit margin of the task s_i is greater than the threshold T. If positive, the user u_i selects the task; otherwise, the user u_i drops out.

4.4 Incentive mechanisms

There are 9 incentive mechanisms studied in this report. The task-reverse-auction (TRA) incentive mechanism has been discussed in the literature [15–17]. It is known that the task-reverse-auction incentive mechanism cannot guarantee that all tasks are completed within a short total operation time in untruthful bid scenarios [16]. Our incentive mechanism design has a goal to reduce the total operation time. Thus, we will compare their total operation times in Section VI. The other 8 incentive mechanisms are described as follows.

4.4.1 Static Uniform (SU) incentive mechanism

In static uniform incentive mechanism [12], the incentives of sensing tasks are fixed values that are uniformly distributed and have the value R_{ij} calculated by (3). In this case, R_{ij} is set to the base reward BR.

$$R_{ij} = \frac{B}{|S|} = BR \tag{3}$$

Algorithm 1: Platform-driven greedy algorithm

```
Input: u_i, S_a, T where u_i =< s_j, a_i, C_ij, x_i, y_i >
Output: Updated u_i.s_j
if S_a == ∅ then
    u_i.s_j = −1 // user u_i drops out as no task is available
    return
MP = −∞, CR = −∞
for s_j in S_a do
    P_ij = R_ij − C_ij
    if P_ij ≥ MP then
        MP = P_ij
        CR = R_ij
        s = s_j
if u_i.a_i == 0 then
    NPM = 100 × (MP+CR)/CR
else
    NPM = 100 × (MP+u_i.a_i)/(u_i.a_i)
if NPM < T then
    u_i.s_j = −1 // u_i drops out as no task gives ample profit
    return
u_i.a_i = u_i.a_i + CR
u_i.s_j = s
return
```

4.4.2 Dynamic Relative (DR) incentive mechanism

The incentives change their values R_{ij} based on the distance from currently unavailable users and the user u_i to the sensing task s_j. This incentive mechanism ranks the currently unavailable users and user u_i by their distance to the sensing task s_j in an increasing order. Then, the value of incentive for the sensing task s_j can be calculated by (4).

$$R_{ij} = \begin{cases} BR & k_i = 1 \\ BR(1 - \frac{1}{2}\frac{k_i}{|U|}) & k_i \geq 2 \end{cases} \tag{4}$$

4.4.3 Dynamic/Static User Centric (DUC/SUC) incentive mechanisms

First, the center of user locations is calculated by (5). Then we compute the distance $d_{s,uc}$ from the task s to the user center by (6). The value R_{ij} is inversely proportional to the distance as shown in (7).

- Static case: rewards of sensing tasks are computed only once at the beginning of each trial.
- Dynamic case: it is similar to the static case, but the only difference is that the calculation repeats whenever a user is about to select a sensing task.

$$(x_{uc}, y_{uc}) = (\frac{\sum_{i\in U} x_i}{|U|}, \frac{\sum_{i\in U} y_i}{|U|}) \tag{5}$$

$$d_{s,uc} = |x_s - x_{uc}| + |y_s - y_{uc}| \tag{6}$$

$$R_{ij} = BR(1 - \frac{1}{2}\frac{d_{s,uc}}{b * 2}) \tag{7}$$

4.4.4 Dynamic/Static Task Centric (DTC/STC) incentive mechanisms

First, the center of user locations, i.e. tc, is calculated by (8). Then we compute the distance $d_{s,tc}$ from the sensing task s to the sensing task center by (9). The value R_{ij} is inversely proportional to the distance as shown in (10).

- Static case: rewards of sensing tasks are computed only once at the beginning of each trial.
- Dynamic case: it is similar to the static case, but the only difference is that the calculation repeats whenever a user is about to select a sensing task.

$$(x_{tc}, y_{tc}) = (\frac{\sum_{s \in S} x_s}{|S|}, \frac{\sum_{s \in S} y_s}{|S|}) \tag{8}$$

$$d_{s,tc} = |x_s - x_{tc}| + |y_s - y_{tc}| \tag{9}$$

$$R_{ij} = BR(1 - \frac{1}{2}\frac{d_{s,tc}}{b * 2}) \tag{10}$$

4.4.5 Dynamic/Static Pit (DPIT/SPIT) incentive mechanisms

In this pit-based incentive mechanism, we use all the users' coordinates to calculate an average distance to the sensing task s by (11). Then, we compute the incentive R_{ij} of the sensing task s by (12).

- Static case: rewards of sensing tasks are computed only once at the beginning of each trial.
- Dynamic case: we need to recalculate the incentives when a user is about to select a sensing task.

$$avg_s = \frac{\sum_i (|x_s - x_i| + |y_s - y_i|)}{|U|} \tag{11}$$

$$R_{ij} = \frac{BR}{2}(1 + \frac{avg_s}{b * 2}) \tag{12}$$

5 Simulation Settings

5.1 Parameters

The parameter tuple for each trial is $< B, P, IM >$. After simulations, the evaluation metric tuple $< t_f, PC >$ will be averaged across the total number of simulation trials. In our simulation, the unit of time and money are time unit and fiat unit. Here is the description of the parameters of the experiments:

- Budget B represents the quantity of money that allow the platform to use in a trial. For this experiment, 100 data points were collected in the interval $B \in [100.00, 1090.00]$ with 10.00 spacing between each data point.

- Area coverage percentage P represents the percentage of the area that requires sensing data. Similar to the budget, 100 trials were conducted such that $P \in [20.0\%, 79.4\%]$ and that there was 0.6% spacing between each data point. This interval represents a wide range of possible target percentages for pavement crowdsensing. Note that we round down the area coverage percentage when calculating the number of tasks.

- The final parameter is the incentive mechanism IM used in the trial. The different IM calculate rewards of tasks differently.

5.2 Simulation execution

Given $< B, P, IM >$, the construction phase initializes the numbers of cells, users, and sensing tasks in the following order:

- For each cell, any references to users or sensing tasks are cleared.

- For all users, s_j, a_i, C_{ij}, x_i, and y_i are initialized. s_j is set to 0. Each user would be placed in a cell randomly without overlapping.

- For all sensing tasks, u_i, R_{ij}, x_j, and y_j are initialized. u_i is set to 0. Each sensing task will be placed in a cell randomly with no overlap between other sensing tasks.

In the execution phase, available users start their turns by selecting and committing to a sensing task based on Algorithm 1. Then, the user will update its s_j. In turn, the user information associated with the sensing task s_j will be updated to reflect that the user u_i now performs task s_j. If no suitable sensing task is found, then the user drops out of the trial for all future turns. Unavailable users are the ones who have not dropped out and are committing their turns by moving towards their sensing tasks. If the user lands on the sensing task, then a_i increases by R_{ij}. If the user is not on the sensing task, then the user must wait another turn to move closer. In both cases, C_{ij}, x_i, and y_i are updated to reflect the current user location.

6 Results

Incentive mechanisms are evaluated and compared in three scenarios corresponding to low, medium, and high area coverage percentages for pavement crowdsensing with different numbers of users. The platform cost is used to order the incentive mechanisms based on their performance data as shown in the following figures. The minimal budgets shown in the figures are the lowest budgets that can realize a 100% success rate for the targeted area coverage percentage. It means that any budgets higher than this value allow the platform to achieve the 100% success rate for the targeted area coverage.

6.1 Platform cost comparison

In this subsection, we discuss the comparison of incentive mechanisms in terms of the platform cost.

- Given 25% area coverage, Fig. 1 shows that the SU and DR incentive mechanisms respectively have the lowest platform costs when the platform has 3 users and 15 users. Apart from this, the static and dynamic pit incentive mechanisms always rank among the top three incentive mechanisms in all scenarios.
- Given 50% area coverage, Fig. 2 shows that static and dynamic pit incentive mechanisms still have the best performances of the platform cost in all scenarios. Even though the DTC incentive mechanism achieves the lowest platform cost in *50% area coverage with 45 users*, this observation does not conflict with the previous statement.
- Given 75% area coverage, Fig. 3 shows that SPIT and DPIT always have the lowest platform cost regardless of how many users the platform has.

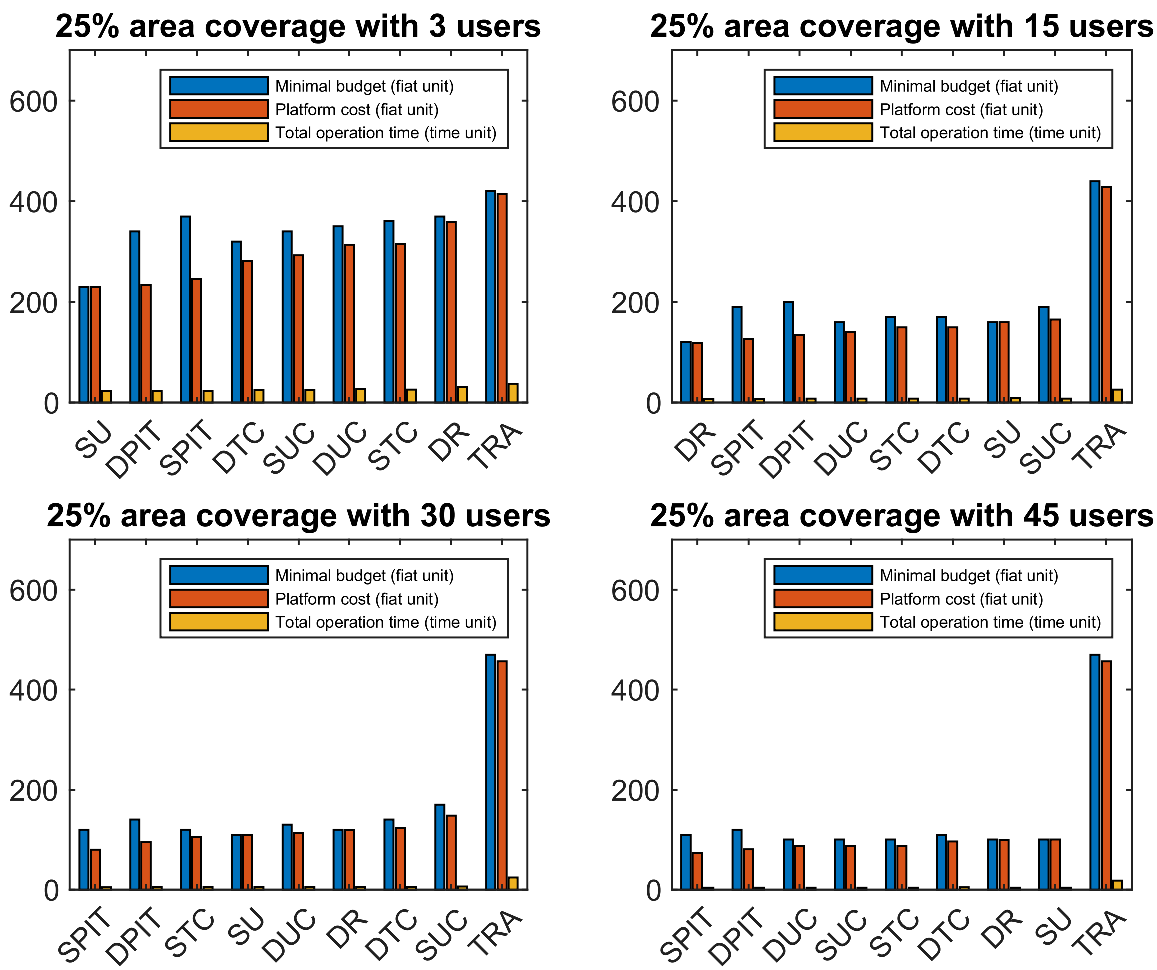

Figure 1: Incentive mechanism comparison: 25% area coverage

Based on the observations described above, we can conclude that SPIT and DPIT are two incentive mechanisms that have the lowest platform cost.

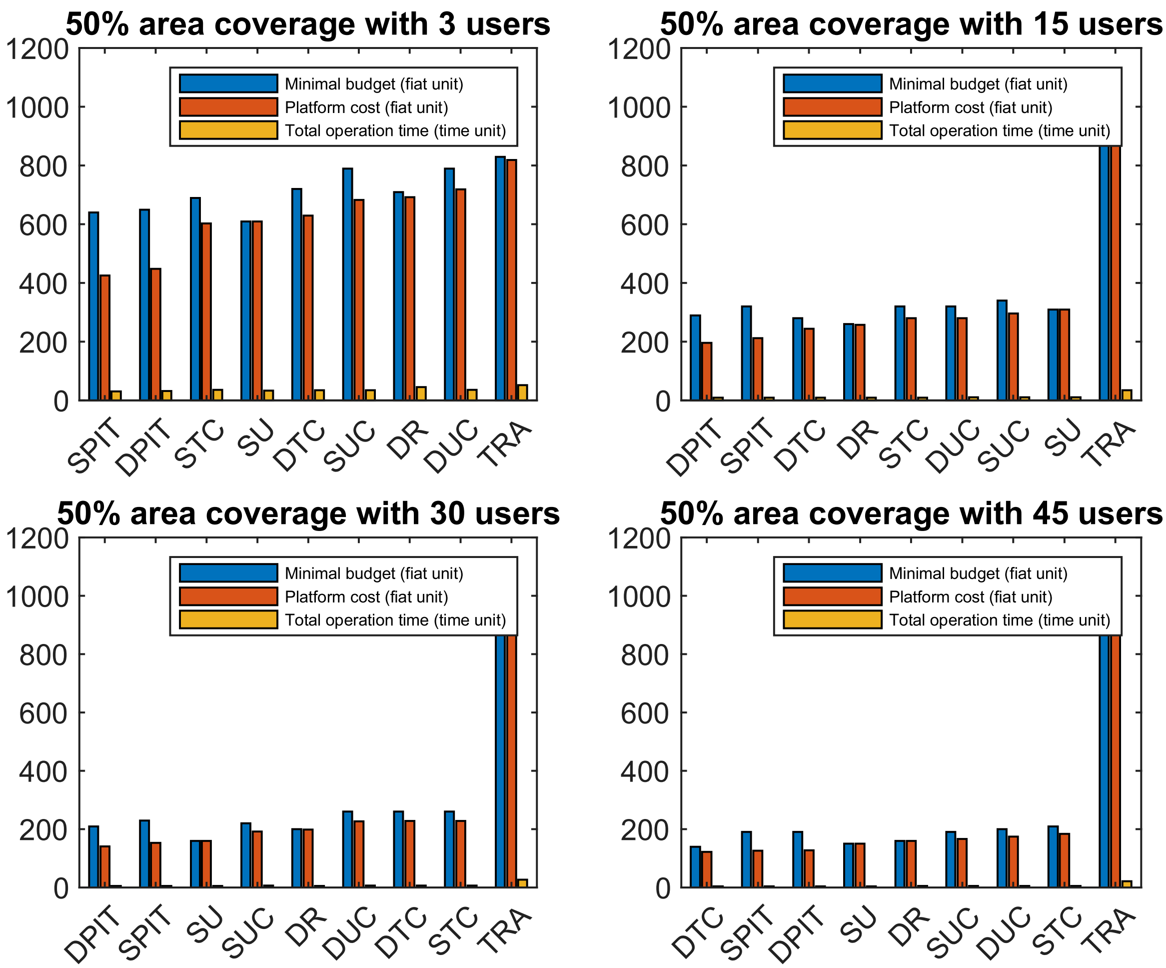

Figure 2: Incentive mechanism comparison: 50% area coverage

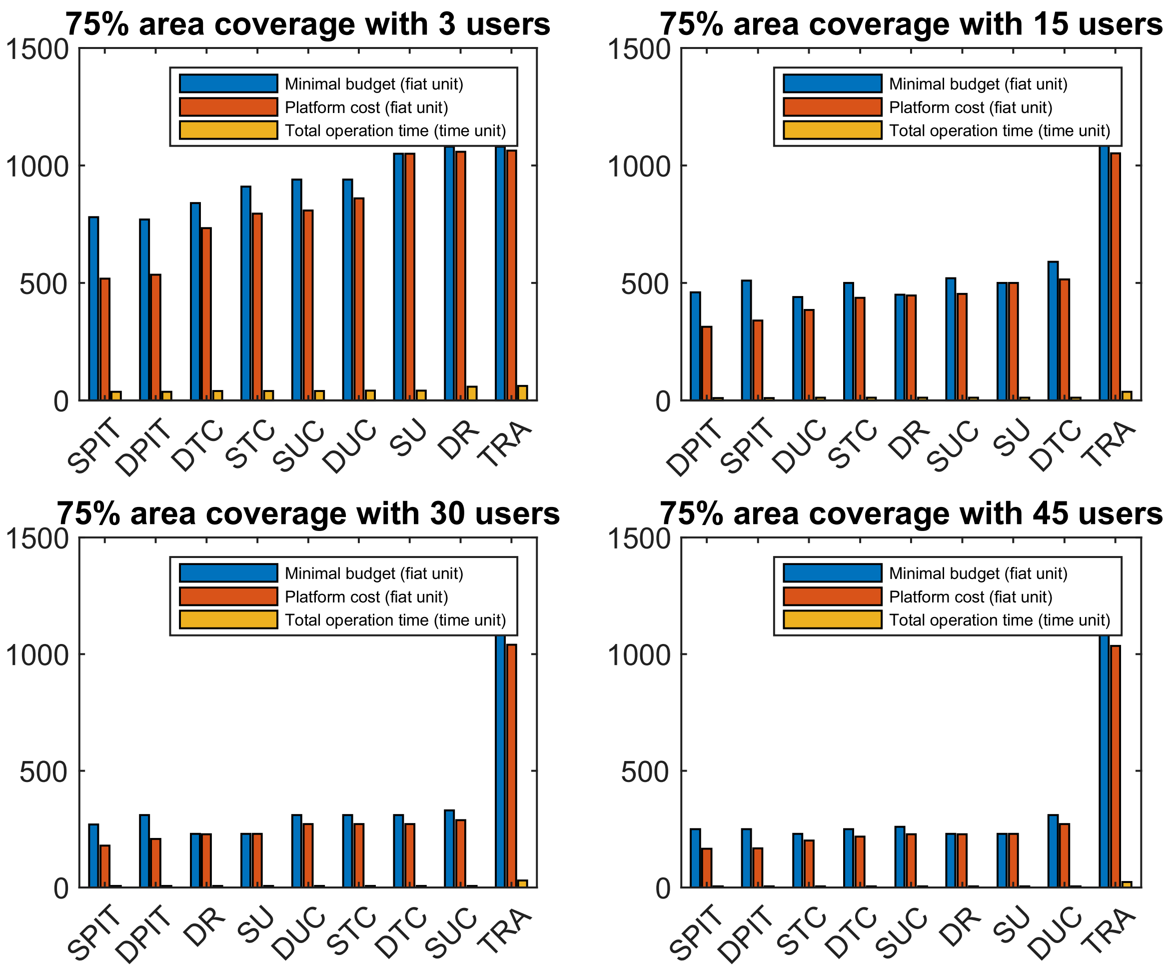

Figure 3: Incentive mechanism comparison: 75% area coverage

6.2 Total operation time comparison

In this subsection, we discuss the comparison of incentive mechanisms in terms of the total operation time. From Figs. 1, 2, and 3, the total operation time of the task-reverse-auction (TRA) incentive mechanism is nearly twice as the total operation times of ours. Additionally, the total operation time of the TRA incentive mechanism becomes longer as the number of participatory users increases while the total operation times of our incentive mechanisms would decrease in the same situation. Therefore, this result proves that our incentive mechanisms have much less total operation time than the task-reverse-auction (TRA) incentive mechanism.

7 Conclusion and Future Work

In this report, we proposed eight incentive mechanisms based on a platform-driven greedy algorithm to help the crowdsensing platform motivate users to collect pavement condition data. Since our incentive mechanisms allow users to select the sensing tasks based on a platform-driven greedy algorithm before they start to collect the data, they can avoid the cost explosion problem observed in the data-reverse-auction incentive mechanisms. From the simulation results, we find that SPIT and DPIT are the incentive mechanisms that have the lowest platform cost. Compared with the task-reverse-auction incentive mechanism, our incentive mechanisms reduce the total operation time by half. Our future research includes large-scale simulations and real-life experiments by extending our prototype pavement crowdsensing system.

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APPENDIX II

WiP: Crowdsensing for Pavement Monitoring with a Blockchain-based Incentive Mechanism

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***Abstract*—Crowdsensing is the umbrella term for the idea of individuals, or rather "crowds", contribute data through "sensing" for a common interest. We have designed and implemented a crowdsensing system solution for low-cost and scalable pavement monitoring. This work-in-progress paper describes a new concept of a "bring-your-own-CPU-and-algorithm" policy based on blockchain to address the challenges of privacy preservation, data integrity, and incentivizing participation in crowdsensing.**

I. Introduction

A. Problem Statement

Nationwide, over 19% of the roads are in poor conditions and require repair, which consequently leads to loss of billions of dollars a year in congestion and delays. This results in an extra 3.1 billion gallons of fuel wasted. It is desirable to constantly monitor the pavement condition of the road network so that preventive maintenance can be timely scheduled and performed. The task of detecting, classifying and tabulating data of pavement conditions is a tedious task. With 4.18 million miles of road in the United States, it is intuitively time consuming and cost intensive to monitor the conditions of such a large transportation network. As 77% of this mileage is maintained by local governments, 19% by state, and 4% by federal and due to budget constraints, a large portion of the road networks are not monitored.

B. Crowdsensing and its Challenges

There are existing research and solutions that make the road pavement monitoring more efficient, e.g. transforming it from manual pavement distress detection and classification to automatic processing [1], taking advantage of connected vehicle data [2], using smart phones for continuous road condition monitoring [3][4], and detecting pavement defects based on entropy [5]. For example, Roadroid [4] and RoadLabPro [6] make it possible to provide a crowdsensing solution to pavement monitoring and preventive maintenance covering the whole road networks in a cost-effective way.

However, surveys of mobile crowdsensing [7] [8] show that there are many challenges that need to be addressed by the state of the art, such as privacy preservation, data integrity, and incentivizing participation.

C. Contributions

In our research we design and implement a crowdsensing system for road pavement monitoring. We propose and study a new concept of a "bring-your-own-CPU-and-algorithm" policy based on blockchain to address the challenges of privacy preservation, data integrity, and incentivizing participation in crowdsensing.

II. Crowdsensing System Solutions

The mobile application of the crowdsensing system is capable of capturing images of road pavement conditions, processing them using machine learning (ML) algorithms, and uploading corresponding sensor data including image and location information of the detected pavement problems to the backend. Such information is stored in a structured manner in the backend that can be easily queried or further processed. The backend also provides the hosting and business logic of an administrative interface. Figure 1 shows the snapshots of pothole detection (left), crack detection (top right), and visualization of the administrative interface.

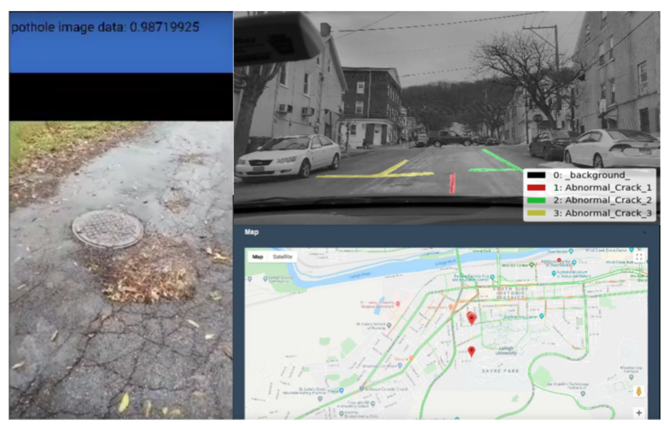

Fig. 1. Pothole and Crack Detection and Administrative Dashboard

III. A New Incentive Mechanism for Crowdsensing

When using of blockchain in the crowdsensing of pavement monitoring, the main value added derives from the intersection between machine learning (ML) and blockchain. With a centralized model, the central system is responsible for procuring the graphics processing power to run the machine learning (ML) algorithm on all the images to be processed. This approach does not scale well. A decentralized approach with incentive mechanism based on blockchain, however, can potentially accomplish two improvements in this regard.

A. Crowdsourcing Data Processing Algorithm and Power

A "bring-your-own-CPU-and-algorithm" policy would simply "crowdsource" the two resources that are bottlenecks in the crowdsensing system design. A model where participants compete to see who can have the best algorithm and/or computing capability, in exchange for cryptocurrency reward. In this scenario, there is no longer any need to amass any significant hashing power in house, and the algorithm no longer needs to be developed in house. ML algorithms "learn" from the data they process, so here both the data and the algorithm are crowdsourced. For example, if a participant's ML algorithm can correctly classify the entire blockchain of images of pavement conditions so far as well as some number of additional images that are to be added to the dataset, and is also the first to do so, the participant is rewarded with cryptocurrency. This way the ML is constantly improving its own substance and expanding its data set, with its computational labor being fully distributed among its participants.

B. Data Integrity

A chain is as strong as its weakest link, and the blockchain is no exception. If someone were to compromise the integrity of this system, they could very well automate its exploitation, and rapidly amass ill gotten cryptocurrency, which is why the sanitization of the initial input data such as images is crucial. Therefore this system is not free of responsibility. Given the nature of a model that compensates based on contribution, there will of course be users who seek to cheat. For example, a user could potentially supply fake images from outside the official client app, leading everyone to believe that there are potholes where there aren't any. To prevent this, the client app and blockchain system will need to have measures in place to ensure the integrity of the input data. One avenue to pursue is by having the client app embed a unique signature using one-way cryptography so that every node in the network can verify that the origin of the image was the official client app. There exists studies using blockchain to verify the integrity of videos recorded from an Android device, with a 98.1% accuracy, thereby proving that such a measure is possible [9].

C. Ethereum based Implementation

Ethereum, one of the larger cryptocurrencies, is known for its distributed application (dApps) platform. The underlying blockchain for this project has so far been implemented using a private Ethereum network. Participants can mine, and thereby process research data, by running an Ethereum compatible "full node". Nodes are "full", if they enforce all rules of the network. Participants can act as a full node for this project by using any Ethereum full node software. This project has been tested using Geth, which is a command line interface written in Go.

The project's private Ethereum network supports transactions, so participants can freely move the project's generic currency in the same manner as one would send official Ethereum cryptocurrency, using either Ethereum compatible wallet software, or from the command line. From the full node software, participants can process whatever machine learning workload propagated to it. To test this capability and assess its feasibility for the proposed goals of this project, the network was test driven using a publicly available IMDB sentiment classifier distributed by Microsoft [10]. Using the React dashboard, a workload can be added to the blockchain, and participants who are mining can supply a sentiment prediction in exchange for reward. Given that the underlying blockchain is not bound to any particular machine learning algorithm, the project gains versatility in that the framework can seamlessly be adapted to any machine learning workload simply by propagating that workload to the network for active full nodes to mine. The pavement monitoring machine learning algorithm is inherently suitable for use on this network, with the only caveat being the security concern discussed above, which needs to be addressed prior to user adoption.

IV. Conclusion and Future Work

In this research we design and implement a mobile crowdsensing system for road pavement monitoring. Machine learning models are used in sensing data analysis in a distributed manner. We have proposed crowdsourcing data processing algorithms and related computation powers based on blockchain. Ongoing and future research work will focus on evaluations of this blockchain-based incentive mechanism for crowd participation, data integrity and privacy preservation.

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