Improving Sensing Coverage in Vehicular Crowdsensing using Location Diversity

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***Abstract*—The massive use of vehicles as a primary means of transportation as well the increasing adoption of vehicles' on-board sensors represents a unique opportunity for sensing and data collection. However, vehicles tend to cluster in specific regions such as highways and a few popular roads, making their utilization for data collection in isolated regions with low-density traffic difficult. We address this problem by proposing an incentive mechanism that encourages vehicles to deviate from their pre-planned trajectories to visit these isolated places. At the core of our proposal is the idea of compensation based on participants' location diversity, which allows for rewarding vehicles in low-density traffic areas more than those located in high-density ones. We model this problem as a non-cooperative game in which participants are the vehicles and their new trajectories are their strategies. The output of this game is a new set of stable trajectories that maximize spatial coverage. Simulations show our approach outperforms the approach that doesn't take into account participants' location diversity in terms of spatial coverage and road utilization.**

I. Introduction

Mobile crowdsensing (MCS) is a new paradigm that leverages people's massive adoption of mobile and pervasive devices for data collection purposes [1], [2]. Here, a platform recruits a set of participants who agree to use their mobile sensors to collect sensing data based on a particular sensing request. Participants commit to sensing campaigns at different levels of engagement, a high burden (participatory) in which data collection requires an active user's involvement or a light burden (opportunistic) where participants may not be aware of their active application [3]. The former approach involves people in significant decision-making where participants have to execute physical actions to collect data. These may include pushing a button, taking a picture, and activating or deactivating a sensor. In the latter approach, which is the focus of this work, the participants' daily routine is not interrupted, and the vehicle's sensors are utilized whenever their state matches the requirements of the sensing application. Here, a participant's agent computes the utility of using its sensors for a given sensing task and authorizes its use if it is sufficiently compensated.

In terms of the type of participants, MCS has been traditionally associated with pedestrians who agree to use their smartphones for data collection. In this context, the synergy that results from the collective participants' behavior resembles a mobile sensor network; where nodes correspond to individual participants and the network mobility depends on the participants' mobility patterns. Here, the crowdsensing application determines the best type of participant for the sensing task. For instance, in the case of monitoring road networks and infrastructure [4], traffic prediction [5], map creation and updating [6], and the monitoring of variables of interest in large and extensive areas, vehicles are a better fit than pedestrians given the large and extensive areas covered by their mobility patterns.

In this work, we focus on Vehicular Crowdsensing (VCS) as a natural extension of MCS where participants are vehicles that use their on-board sensors to collect sensing data. Thus, VCS is about continuous sensing rather than discrete sensing tasks, namely, coverage is based on vehicles' sensing trajectories which is the focus of this work.

We focus on the problem of attracting sensing workers (vehicles) to isolated areas with low traffic densities. This is a problem that affects MCS in general, and it is exacerbated in VCS due to the predictability of vehicles' trajectories [7]. Unlike pedestrians who easily modify their trajectories on the fly, vehicles' trajectories are usually set beforehand using GPS navigation systems. As a result, most of the traffic flows through the same few popular roads, limiting the use of vehicles for crowdsensing purposes. In contrast, in an ideal scenario, vehicles would spread through the road network collecting a representative set of sensing samples useful to estimate the variable of interest with high accuracy. We tackle this problem by designing an incentive mechanism for VCS that encourages sensing coverage based on location diversity. A concept we will explain in detail in Section III-A1

In particular, a participant's utility function follows a general platform-based approach, namely the difference between a reward that is proportional to the participant's contribution, and the cost in which the participant incurs for providing that contribution [8], [9].

In the context of this work, a participant obtains a reward that is proportional to its spatial diversity. On the other hand, platform utility is maximized when participants provide high diverse spatial data.

At the core of our approach are the utility functions for both participants and the platform. We design these functions to incentivize vehicles to travel and collect samples from places with low participant density. Thus, the vehicles' utility is inversely proportional to the vehicular's density of the region they travel. In other words, the platform encourages participants to deviate from crowded places (low diversity) to visit isolated places (high diversity) to maximize their utilities. We model this problem as a non-cooperative game in which players include a platform or data buyer and a set of participant vehicles or contributors. Here, the platform sets a reward, and participants compete against each other to maximize their portion of that reward. Here, a participant's strategy corresponds to its location's spatial diversity, namely the amount of deviation from its original trajectory needed to build a new trajectory that maximizes its spatial diversity. The output of this game is the Nash Equilibrium participants' spatial diversity. Here, each value of R induces a unique Nash Equilibrium spatial diversity. Thus, environmental agencies and city planners can adjust the data quality in terms of data spatial diversity when outsourcing sensing data collection by tuning the value of the offered reward.

The followings items summarize the paper's main contributions:

- We designed a VCS incentive mechanism based on the concept of spatial diversity.
- We formulated the concept of spatial diversity based on the Frechet distance.
- We formulated the deviation trajectories Nash Equilibrium.
- We evaluated our algorithms using a real-traffic simulator (SUMO), and OpenStreet Maps

II. Background and related work

A seminal paper on the use of vehicles for sensing and data collection is the work He *et al.* [7]. Here, the authors propose to predict the participants' future trajectories and acquire the combination of them that maximizes coverage within a limited budget. Unlike our work, this proposal does not incentivize vehicles to deviate from their ongoing trajectories, thus limiting the potential coverage improvements provided by the deviations. Similar to the work of He, the work of Wang *et al.* [10] focuses on participants' recruitment based on probable future trajectories. However, the authors here focus on optimizing recruitment cost, rather than coverage quality under a limited budget. Following a similar approach, namely sensing coverage based on participants sensing trajectories, Kong and Chen *et al.* [11], [12] present recruiting frameworks based on the acquisition of segments rather than entire participants trajectories. Here, the authors approximate the solution of the problem of covering the space using the subset of trajectories at minimum cost.

Another important contribution to VCS corresponds to the work of Gao *et al.* [13]. Here, the authors propose a reverse auction-based data acquisition in a non-deterministic crowdsensing environment. In this scenario, participants bid in advance for several sensing tasks which must be completed at certain time intervals. Then, the platform computes the probabilities of successful completion of each task per participant, and then uses this information along with the proposed bid price for participants recruitment. Similar to our proposal, Chakeri *et al.* [9] introduces a game theoretical-based incentive mechanism for VCS that encourages vehicles to deviate from their pre-planned trajectories in order to visit places of sensing interest. Unfortunately, this synchronous model does not consider the cost of deviation, and it was tested in an unrealistic grid environment.

The work of Chintakunta *et al.* [14] also follows a game-theoretical approach, but this time with the primary goal of maximizing temporal coverage. In this work, the authors, designed utility functions for both the platform and the participants. Here, participants increase their utilities when collecting data at regular time intervals. The aforementioned work is similar to our current proposal in the sense that participants deviating from their ongoing trajectories may increase spatial coverage. However, this is just a sub-optimal by-product given that the main goal here is to maximize temporal coverage. In addition, here sensing tasks are discrete and isolated, while our proposed work uses sensing trajectories in order to provide spatial coverage.

III. System model and implementation

The system consists of a sensing platform and a set of participants that are vehicles with their respective source and destination. The vehicles are equipped with sensors which are making measurements along their paths (sensing traces). The goal of the platform is to incentivize the vehicles to deviate from their path to improve the overall spatial coverage of measurements resulting from these sensing traces.

In order to simplify the task at hand, we assume all vehicles start from their source location at the same time, and their sources and destinations are reported to the sensing platform. The sensing platform then computes a modified route for all the vehicles. Any vehicle that has to deviate from its original route will be rewarded. The reward will depend both on the amount of deviation, the vehicle's location diversity, and the routes assigned to other vehicles. The utility attained by the vehicle would then be the reward minus the cost of deviation. The platform ensures that the route assignment comprises a Nash equilibrium, which in turn ensures fairness and compliance from the vehicles. We now proceed to formalize the notions mentioned above.

A. Vehicles

The set of vehicles is denoted by $w = \{w_1, w_2, \ldots, w_M\}$. The source and destination of w_i are represented by s_i and d_i respectively. w_i's default trajectory is defined as the set of edges with the minimum cost (in terms of distance) between vertices s_i and d_i.

1) Location diversity: High vehicle density in a given area increases the supply of sensors in that area thereby reducing the cost of their measurements. The platform therefore wants to reward vehicles in low vehicle density areas higher relative to those in high vehicle density areas. We capture this notion by *location diversity* of the vehicle's route which intuitively should be a decreasing function of vehicle density. We will quantify the location diversity of a vehicle's route based on how "spatially different" it appears from the route of other vehicles. One such quantification which is very appropriate in this situation is the notion of Frechet distance [15], [16].

We can think of vehicle trajectories as curves on a two-dimensional plane. Frechet distance measures the distance between the curves. Given two curves $r_i, r_j : [0,1] \to \mathbb{R}^2$, the Frechet distance is given as

$$d_F(r_i, r_j) = \inf_{\alpha,\beta} \max_{t\in[0,1]} d(r_i(\alpha(t)), r_j(\beta(t))), \tag{1}$$

where d is the Euclidean distance between two points, and the infimum is taken over all parameterizations of the curves. A common analogy used to provide intuition for Frechet distance is as follows (from Wikipedia): *"Imagine a person traversing a finite curved path while walking their dog on a leash, with the dog traversing a separate finite curved path. Each can vary their speed to keep slack in the leash, but neither can move backwards. The Fréchet distance between the two curves is the length of the shortest leash sufficient for both to traverse their separate paths from start to finish."*

We define the location diversity of a route r_i of the vehicle w_i as

$$x_i = \frac{1}{\sigma \sum_{j\neq i} e^{-\frac{d_F(r_i,r_j)}{\rho}}}. \tag{2}$$

where σ and ρ are tuning parameters. The summation in the denominator is over all other routes. x_i measures how "far" route r_i is from all other routes. Say there is another route r_j with a small $d_F(r_i, r_j)$, this will increase the denominator thereby decreasing x_i. The function is selected such that routes which are very far away does not have a significant impact on the diversity value. This ensures that we don't get small diversity values in the case where there are large number of routes far away. At time $t = 0$, all vehicles transmit their route information to the platform, which then sends back an alternative route. This process in described in the following section.

Figure 1 is an example heat map showing the diversity values of various trajectories. In this scenario, we divide a total of 150 vehicles into 3 different groups, 80% of the participants travel the diagonal routes, while the other 20% are evenly distributed among other other two groups. With this setup, we expect the diagonal routes to have low diversity value, while the other two groups to have higher diversity. The figure shows that the diversity values calculated are as expected. The routes in the diagonal show low diversity values (tending towards blue) and the routes along the edges have high diversity values (tending towards red).

B. Platform

The platform's goal is to improve the overall spatial coverage (its utility) by incentivizing the vehicles to deviate form their paths so as to cover more area.

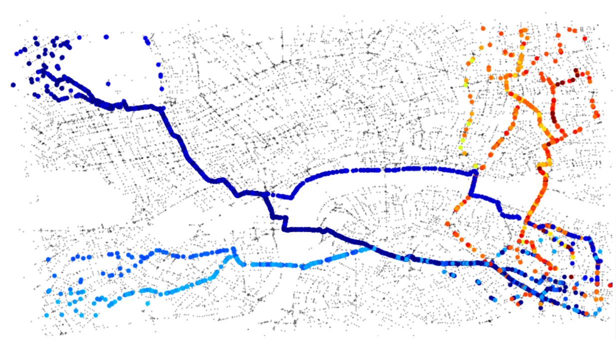


Fig. 1: Diversity heat map computation on a set of vehicles' trajectories. The diagonal routes (with large number of vehicles) have low diversity values and the routes along the edges have high diversity values.

1) Platform utility: Given a coverage area $\mathcal{C}$ within which the vehicles are travelling, the spatial coverage of the measurements is defined as

$$U = \frac{1}{\int_{\mathcal{C}} d^2_{\{r_i\}} dA}. \tag{3}$$

The denominator in equation 3 is the area integral of the function $d^2_{\{r_i\}}$. For a given point $c \in \mathcal{C}$, $d_{\{r_i\}}(c)$ is the smallest Euclidean distance between c and all the routes. We are using $d^2_{\{r_i\}}$ instead of $d_{\{r_i\}}$ to represent inverse square relationship between the distance and sensing quality degradation for most sensors.

2) Vehicle utility: The platform rewards the vehicles by distributing a set amount of money R amongst all vehicles. If the reward for the vehicle w_i is R_i, then we have $\sum_i R_i = R$. In order to incentivise the vehicle to deviate, the reward R_i is proportional to the deviation t_i (in distance) vehicle w_i is taking from its original route. Furthermore, if multiple vehicles are traversing the same or similar routes, then small deviation from all of them will have a combined effect of a large deviation. Whereas, if there are very few vehicles on a specific route, then it would be beneficial for the platform for those vehicles to deviate more. Therefore, the reward R_i is also set to be proportional to its diversity x_i as computed in equation 2. Let $\mathbf{t} = (t_1, t_2, \ldots, t_M)$ be the set of deviations assigned to the vehicles. Taking this discussion into consideration, the vehicle utility is defined as

$$u_i(\mathbf{t}) = \frac{t_i x_i}{\sum_i t_i x_i} R - c_i t_i, \tag{4}$$

The first term in equation 4 is the reward R_i and the second term is the cost. Note that the cost is proportional to amount of the deviation. The parameter c_i can be negotiated by w_i to indicate its willingness to participate in the program. The utility u_i for any vehicle w_i in equation 4 depends not only on the deviation of w_i, but on the deviations of all other vehicles.

We want to find a set of deviations $\mathbf{t}^* = (t_1^*, t_2^*, \ldots, t_M^*)$ such that $u_i(\mathbf{t}^*) \geq u_i(\mathbf{t})$, $\forall \mathbf{t} \neq \mathbf{t}^*$, and $\forall i$. This means that the utility for each vehicle is the best it can be given the deviations of all vehicles. From the vehicles' point of view, such an allocation appears fair and there is no incentive for any one vehicle to not comply with this allocation. In game theory, such an allocation is called a *Nash equilibrium.*

The vehicle utility in equation 4 is very similar to that found in Yang *et. al.*[8], where they formulate a sensing game with the utility for the i^{th} participant as

$$u_i^j = \frac{t_i^j}{\sum_i t_i^j} R - k_i^j t_i^j, \tag{5}$$

where t_i is the amount of time the i^{th} participant spends in performing the sensing for j^{th} crowdsourcer, R is the total platform reward available, and c_i is the cost per unit time. Yang *et. al.*[8] showed that the game with utility function as in equation 5 has a unique Nash equilibrium, and also provided an algorithm to find the Nash equilibrium which we replicate here as Algorithm 1.

If we substitute $s_i = t_i x_i$ in equation 4, the resulting utility will be equal to

$$u_i(\mathbf{s}) = \frac{s_i}{\sum_i s_i} R - \frac{c_i}{x_i} s_i \tag{6}$$

which is exactly the same as equation 5 allowing us to use Algorithm 1 to find the Nash equilibrium deviations.

The input to Algorithm 1 is the set of costs $k_1^j, k_2^j, \ldots, k_{w_j}^j$, where j identifies a specific crowdsourcer in a set of crowdsourcers. Since we only have a single crowdsource, the superscript is not relevant to the work here. The costs k_i^j correspond to c_i/x_i in equation 6, and w_j corresponds to the number of vehicles M. The output of the algorithm is the set of Nash-equilibrium sensing times $\left((t_1^j)^*, (t_2^j)^*, \cdots, (t_{w_j}^j)^*\right)$, which correspond to s_i in equation 6. The Nash-equilibrium deiverations t_i can then be obtained as $t_i = s_i/x_i$.

Algorithm 1 Computation of the Nash equilibrium Sensing Plans for Participant w_i

```
Sort the set of contributors W_j (|W_j| = w_j) in crowdsourcer j according to their costs,
    k_1^j ≤ k_2^j ≤ ··· ≤ k_{w_j}^j;
H ← {1, 2}, i ← 3;
while i ≤ w_j and k_i^j ≤ (k_i^j + Σ_{l∈H} k_l^j)/|H| do
    H ← H ∪ {i}, i ← i + 1;
end while
for all i ∈ W_j do
    if i ∈ H then
        (t_i^j)* = ((|H|−1)R_j / Σ_{l∈H} k_l^j) (1 − (|H|−1)k_i^j / Σ_{l∈H} k_l^j);
    else
        (t_i^j)* = 0;
    end if
end for
return ((t_1^j)*, (t_2^j)*, ..., (t_{w_j}^j)*);
```

Since these deviations are obtained using the location diversities, we will call the resulting deviations as *Location Diversity Deviations (LDD)*. The platform will transmit LDDs to the vehicles. Our simulations in section IV show that LDDs provide a significantly higher spatial coverage (as in equation 3 compared to the case of uniform deviations where all the vehicles are deviating by the same amount. We note here that the processing performed by the platform does not include any route optimization. That is, the platform is only computing the deviations, and not the specific routes which will create these deviations. The vehicles are presumed to chose the routes which will produce the (approximately same) deviations randomly. There is good reason to believe that route optimization will help improve the spatial coverage, but that is a complex problem which will be a focus of our future work. We will emphasize that LDDs by themselves provide good spatial coverage even without route optimization.

IV. Performance Evaluation

In this section, we explain the experimental setup and evaluate the performance of the proposed deviation method. To evaluate the performance of Location Diversity Deviations (LDDs), we compare the impact on improving spatial coverage U (equation 3) with that of a uniform deviation where all vehicles have equal deviations. To keep the comparison fair, we ensure that the total deviation by all vehicles is equal in both cases. We assume all vehicles have equal costs of deviation. The python code for the implementation can be found at the following github repository: https://github.com/flpolyproject/spatialcov.

A. Simulation setup

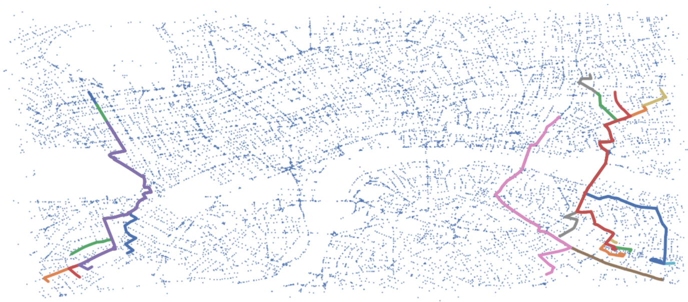
We setup the simulation environment using SUMO [17], a traffic simulator that's capable of making use of realistic map data and simulate mobility behaviors for different modes of transportation. We picked a dense area located around downtown London as our map shown in Figure 1. Using a densely connected street network, the vehicles are opened to many different options when it comes to determine its set of strategies. The map data originates from Open Street Maps (OSM) [18]. SUMO offers great python support through the TraCI api, which allows for management of the traffic simulation at an atomic level. In addition, the Python 3.0 interface of SUMO and TraCI allows for the use of custom Python 3.0 modules that extend the functionality of SUMO. In addtion to TraCI, Networkx is also used to aid vehicle routing for more optimized performance, and the package *similaritymeasures* [19] is used to aid the computation for Frechet distances.

B. Experiment setup

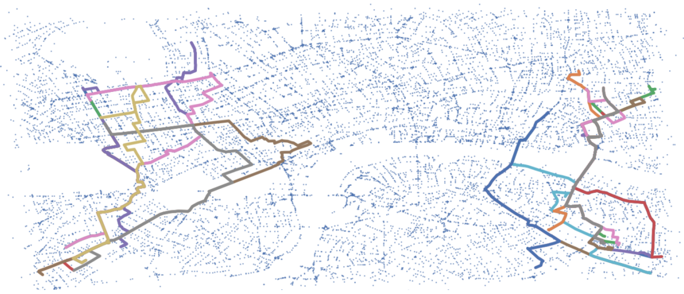
Table I summarises the simulation configurations for the experiments. The sources and destinations of vehicles are randomly selected within a disk of given center and radius. To further maintain fairness within the simulation, the distribution of trajectories are controlled using a set pattern. We divide the total number of trajectories into two groups, with each group residing on either left or right side of the map as shown in figure 2a. Most of parameters mentioned can be found in Table I, and the values can be adjusted for experimental purposes.

TABLE I: Simulation Parameteres

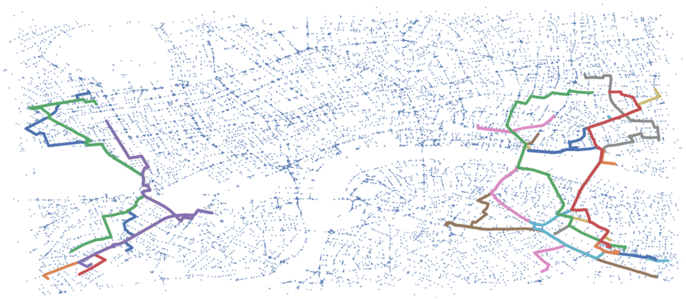
Parameters		**Parameters (cont.)**	
Junctions	14655	Source Radius	1000m
Streets	27937	Destination Radius	1000m
σ	1	Sources	[lower_left, lower_right]
ρ	5	Destinations	[upper_left, upper_right]
Sample interval	10		



(a) Baseline trajectories



(b) Location diversity deviation (LDD) approach



(c) Uniform deviation approach

Fig. 2: An example simulation using $R = 200$, and other parameters in Table I. Figure 2a shows the original routes, 2b shows the routes obtained using LDDs and 2c shows the routes obtained using uniform deviations.

To compute the spatial coverage given in equation 3, we discrete the entire region into equal area squares, compute the function on each and compute the integral numerically.

C. Experiment results

Figure 2 provides a visual validation the proposed approach. The *baseline* routes are shown in figure 2a. This figure shows the initial trajectories of the vehicles. There are 4 trajectories in the left group and 10 trajectories in the right group, implying the location diversities of the routes in the left group are higher than those in the right group. Figure 2b shows the routes obtained using LDDs. As seen in the figure, the routes with higher diversities are deviating significantly more. Figure 2c shows the routes obtained using uniform deviation. The total deviation of all vehicles is the same in figures 2b and 2c.

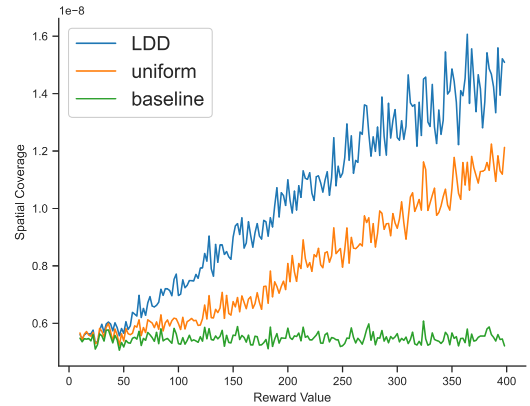


Fig. 3: Figure shows a comparison between LDDs and uniform deviations. Note that LDD based route selection consistently outperforms that based on uniform deviations as the value of R increases.

Figure 3 shows a comparison between LDDs and uniform deviations on the spatial coverage improvement relative to original routes. Here, the reward value is increased from 10 to 400 with a step size of 2. For each reward value, we ran 10 simulations and the result for spatial coverage is averaged over all the simulations. The total number of vehicles used was equal t. When R value (the total reward) is increased, the vehicles respond by taking larger deviations leading to increasing improvements in the spatial coverage as seen in the figure. The figure also shows that LDD based route selection consistently out-performs the uniform deviation.

Figure 4 shows the performance comparison with increasing number of vehicles. The percentage distribution between the two groups is kept the same as the number of vehicles is increased. As seen, the spatial coverage of LDD based route selection consistently outperforms that based on uniform deviation. The R value is kept at 200 in this case.

Another metric of common interest in this field is road utilization, which is computed as the unique number of junctions visited by the vehicles. Figure 5 shows a comparison of the LDD route selection vs uniform distribution on road utilization. As the figure shows, a useful by-product of the approach presented here is an improvement in the road utilization when compared to uniform deviation.

V. Conclusion

In this paper, we introduce and evaluate a incentive mechanism for Vehicular Crowdsensing that encourages trajectory deviation based on location diversity. We presented a incentive mechanism where vehicles traveling on routes with high location diversity are rewarded preferably, and the vehicles deviate

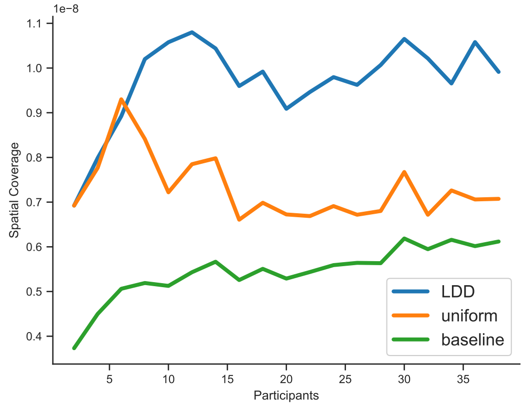


Fig. 4: Participants vs. Spatial coverage

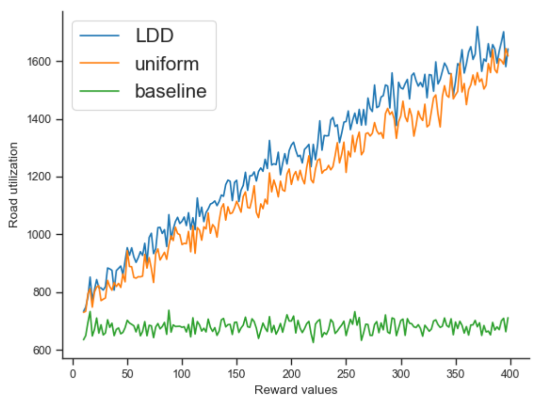


Fig. 5: Reward R vs. Road utilization

according to a Nash equilibrium based on the given rewarding structure. We showed using simulations that when vehicles deviate according to these incentives, the spatial coverage is improved significantly, thus providing an efficient way to use the resources available and obtain high quality sensor measurements from the vehicles in the area of interest.

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