IEEE SoutheastCon 2020

Incentive Mechanism for Vehicular Crowdsensing with Budget Constrains

Xin Wang*, Quentin Goss*, Mustafa İlhan Akbaş†, Alireza Chakeri‡, Juan M. Calderon§¶, Luis G. Jaimes*
*Department of Computer Science, Florida Polytechnic University, Lakeland, FL 33805
{xwang, quentingoss0323, ljaimes}@floridapoly.edu
†Electrical,Computer,Software&Systems Engineering, Embry-Riddle Aeronautical University, Daytona, FL 32114
akbasm@erau.edu
‡Department of Computer Science and Engineering, University of South Florida, Tampa, FL 33620
chakeri@mail.usf.edu
§Computer Science & Engineering Department, Bethune-Cookman University Daytona Beach, FL, USA
calderonj@cookman.edu
¶Department of Electronic Engineering, Universidad Santo Tomás Bogota, Colombia

***Abstract*—In this paper, we present an incentive mechanism for vehicular crowdsensing (VCS) based on a recurrent reverse auction. The proposed approach encourages participant's vehicles to used their sensors to collect data while also maximizing their utility. This approach tackles important issues in VCS such as cost explosion, and area sensing coverage. Using a realistic street network from OpenStreetMaps with extensive SUMO (Simulation of Urban Mobility) simulations, we show our VCS algorithm significantly o utperforms t he b aseline approach in terms of sensing coverage and active number of participants by three and eight times respectively.**

***Index Terms*—Vehicular Crowdsensing, Incentive Mechanism, Coverage, SUMO**

I. Introduction

The massive use of mobile technology and wearable sensors presides the advent of new data collection paradigm called mobile crowdsensing (MCS) [17]. MCS leverages the pervasive use of mobile devises and peoples' mobility patterns to collect sensing samples at a finer l evel o f granularity than tradition methods using isolated meteorological stations. MCS's applications are usually used for collection and report of environment variables such as pollution, temperature [24], pollen, noise [15], etc. In all these cases, the idea is to collect a representative set of sensing samples in order to re-construct a variable of interest.

Vehicular Crowdsensing (VCS) extends the concept of MCS. Here, the data collection process is carried out by sensor attached to autonomous or non-autonomous vehicles (AVs). Given that vehicles travel through road networks, the sensing task is usually based on sensing trajectories rather than in isolated discrete sensing samples [9]. Elements of VCS system include a set of participants and one or several crowdsourcers [27]. Here, participants are a group of vehicles willing to contribute with a set of sensing tasks, and the crowdsourcer recruits a subset of participants that match with the collection requirements. Examples of VCS tasks include route and infrastructure monitoring [4], traffic prediction [23], and map creation and updating [18].

The following summarizes the VCS protocol for data acquisition. A data buyer or crowdsourcer broadcast a request for data collection at time t. Vehicles traveling through the area on interest receive that request via mobile app. The interested participants respond using their apps to send both location coordinates, and sample's price (bid price) to the crowdsourcer. The crowdsourcer receive all the participants' location and bid prices, and selects the subset of samples to acquire using its limited budget. The crowdsourcer communicate this information to the subset of selected participants, who then use their sensor to collected, and send sensing samples back to the crowdsourcer. The crowdsourcer receive the data, and send them back the corresponding payment to participants. This close, what we call a round. This process is repeated at regular time intervals. This methods for data acquisition is called recurrent reverse auction.

In addition to follow this protocol, This work focuses on getting a set of representative sensing samples within a given budget for a given number of rounds. Consider temperature as an example. This environmental variable has a high variability. Thus, in order to provide accurate reports, we need to collect a representative set of samples of a target region, at regular intervals (rounds). In order to get such a set of samples, we take into account both participant location and sample bid's prices.

Our reasoning about participant location takes into account that vehicles' owners are usually located in neighborhoods, and these neighborhoods are usually clustered in terms of both location, and income. Thus, it is natural to assume that the true valuation of participants located in high income neighborhoods may be different from those living in low income regions. In this settings, the use of a reverse auction to acquire sensing

978-1-7281-6861-6/20/$31.00 ©2020 IEEE

samples based on samples' price may end up consuming the crowdsourcer's budget by acquiring a redundant set of samples from low income neighborhoods as shown in Figure 1. On the another hand, if we follow our proposed Incentive Mechanism for Vehicular Crowdsensing with Budget Constrains(IMVCBC) we may get a fewer number of samples. However, these samples are a better representation of the variable of interest as shown in Figure 2.

Fig. 1: Greedy acquisition policy

Fig. 2: IMVCBC acquisition policy

The rest of this paper is organized as follows. Section II corresponds to the related work. We present the system model, and performance evaluation in section III and IV respectively. Finally, Section V concludes this paper.

II. Related Work

Problems such as area coverage and keeping a minimum mass of participants have been a challenge for crowdsensing. Systems addressing these problems have been proposed by authors such Jaimes *et al.* [10] who address the problem of price and user location imbalance by the combination of the Greedy Budgeted Maximum Coverage Algorithm (GBMCA) [11] and the Reverse Auction Dynamic Price(RADP-VPC) [14]. Unfortunately, the authors of this work does not consider vehicles as participants, and the work only focus on pedestrians.

A pioneer paper on VCS corresponds to the work of He *et al.* [9] who propose a mechanism to provide sensing coverage based on a subset of the predicted participants' sensing trajectories rather than on a discrete set of sensing samples. Papers in this category include [8], [27] which propose similar mechanism for reaching sensing coverage, but differ in the solutions of the optimization problem. An extension of these approaches is the idea of providing sensing coverage based on a combination of participants' trajectory segments rather than the entire predicted trajectories. Some works following approach include [3], [12].

Another work on VCS corresponds to the work [28] who use multi-robot planning concepts for participants' trajectories generation, and an auction based-approach for trajectories' acquisition. following a similar approach Xiao *et al.* [26] models the relation between a crowdsourcer and participants as a non-cooperative game. Here, the participants and crowdsourcer strategies corresponds to the sensing accuracy, and a payment policy respectively.

A. Simulation Environments and Mapping Information

The participants of a VCS mechanism exist within a street network (SN). A notable database of SNs is OpenStreetMaps (OSM) [16], which is a common SN format for software such as AOP [22], a tool which increases the amount of vertices in a SN to improve quality of pedestrian movement, the SN visualization tool OSMnx [2], for the crowdsensing simulation tool CrowdSenSim [6], and the traffic simulator SUMO (Simulation of Urban Mobility) [13]. SUMO is software package for traffic modeling and simulation (M&S), with capability of utilizing OSM format SNs, or generating a custom SN. The Python 3.x interface TraCI (Traffic Control Interface) [25] for SUMO enables vehicular M&S. The combination of an OSM SN and SUMO in VCS is seen when Zhu *et al.* [28] utilizes the TAPAS Cologne project [21], a SUMO scenario to evaluate their VCS mechanism. OSM format SNs are common among VCS models and the SN we utilize is sourced from OSM – we utilize a dense sub-network of the OSM dataset with many roads close together that is both necessary and unique to our model, rather than existing SN dataset.

The logic of VCS mechanisms may be computational complex, resulting in slow simulations. Reducing the complexity of the SN through discretization will improve the performance of mechanisms such as ours which frequently query shortest paths on the SN. While components of SNs are discretized in research, such as for the identification of merging and crossing areas [1] and planning of merging scenarios [5] at intersections, or to discretize roads into segments and lanes to roadway usage maximization in connected vehicles [19], a pioneer in discretized SN (DSN) generation is the methodology of Goss *et al.* [7] which considers the spatial and directional information of the SN to generate a DSN that retains important spatial information such as parks, lakes, river, etc. which produces simulation results similar to a non-discretized SN. To improve the performance of our VCS mechanism, we utilize a DSN generated using [7] as the SN in our model.

III. System Model

We propose to cover a region of sensing interest by using a disk model as shown in Figure 3. Here, the center corresponds to the location of the sample offered by a participant vehicle v_i we are considering to acquire at time t. And the disk's radius (R) represents the sensing influence or capacity of the vehicle's sensor. Thus, a high quality sensor would have a larger radius of influence than low quality one. In order to keep the problem simple, we assumed R the same for all participant, and made R a system parameter.

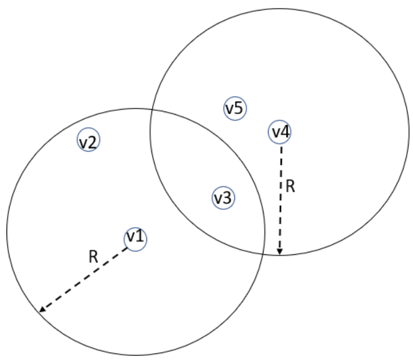

Fig. 3: Disk Covering Model

We combine the geometrical model with the recurrent reverse auction. At each round t, all vehicles bid for their sensing samples at their current locations. The platform receives all bids and by using the geometric model system selects the sample v_i whose disk cover the greatest number of samples at the lowest price. Once v_i is acquired, no other sample is acquired within the disk centered at v_i. We call the samples initially covered by that disk S_i. We call w_i as weight or carnality of S_i, and c_i the cost S_i which corresponds to the cost of v_i. Given the previous notation, now we can state our problem as follows: Given a set U of n elements, a collection $\{S_i\}$, $i = 1, 2, \ldots, n$ of subsets of S and a budget L, we want to find the subset $S' \subseteq S$ such that the total cost of S' does not exceed L, and the total weight of elements covered by S' is maximized. This NP-hard problem, presented by Kuller [11] is known as the Budgeted Maximum Coverage Problem (BMCP). Thus, we model our sample acquisition policy as a BMCP.

A. Sample acquisition and area coverage

Now we present our approach for sensing sample acquisition based on vehicles location and sample price. This approach has the form of the following three functions:

1) Maximize coverage based on the ratio weight-price.
2) Maximize coverage based on weight.
3) Selecting winners.

1) Maximize coverage based on the ratio weight-price: Algorithm 1 loops through U (set of all the subset S_i) building a collection of subsets based on the maximization of $\frac{W'}{c_i}$, where W' denotes the total weight of the elements covered by set S_i, but not covered by any set in G. In other words, acquires the sets of elements that represent the best value for the paid price c_i within a budget L. Finally, the algorithm return the collection of sets G.

Algorithm 1 Maximize coverage based on the ratio weight-price

input: S a collection of sets made up by the user locations
output: $T \subseteq S$, covering set

procedure maxCovByRatio(S) **begin**
  $G \leftarrow \emptyset$
  $C \leftarrow 0$
  $U \leftarrow S$
  while $U \neq \emptyset$ **do**
    if $C + c_i \leq L$ **then**
      $G \leftarrow G \cup S_i$
      $C \leftarrow C + c_i$
      $U \leftarrow U \setminus S_i$
    end
  end
  return G
end procedure

2) Maximize coverage based on weight: Algorithm 2 loops through U building a collection of subsets based on the maximization of W', namely the total number of the elements covered by set S_i, but not covered by any set in G. In other words, acquires the sets with the maximum number of covered samples, constrained to the availability of budget L.

Algorithm 2 Maximize coverage based on weight

input: S a collection of sets made up by the user locations
output: $T \subseteq S$, covering set

procedure maxCovByWeight(S) **begin**
  $G \leftarrow \emptyset$
  $C \leftarrow 0$
  $U \leftarrow S$
  while $U \neq \emptyset$ **do**
    select $S_i \in U$ that maximizes W'_i
    if $C + c_i \leq L$ **then**
      $G \leftarrow G \cup S_i$
      $C \leftarrow C + c_i$
      $U \leftarrow U \setminus S_i$
    end
  end
  return G
end procedure

3) Selecting Winners: Algorithm 3 calls Algorithm 1, and Algorithm 2, These algorithms return the collections (set of sets) G, and G' respectively. Thus, selecting winner algorithm returns the collection with the maximum number of elements.

B. Coverage

In each round the final coverage algorithm finds a $S' \subseteq S$ that covers the greatest possible area covered by S. In areas where the variable of interest is not uniform distributed Figure 1 and Figure 2 how the final coverage works, in the former case the algorithm acquired the first k samples in increasing order of cost, in the latter case the algorithm

Algorithm 3 Selecting winners

input: S a collection of sets made up by the user locations
output: $S' \subseteq S$, covering set

procedure selectWinners(S) **begin**
    $G \leftarrow \emptyset$
    $G' \leftarrow 0$
    $S' \leftarrow S$
    `/* Maximize budget based on the ratio weight-price. */`
    $G \leftarrow$ maxCovByRatio(S)
    `/* Maximize budge based on the weight. */`
    $G' \leftarrow$ maxCovByWeight(S)
    if $|G| \geq |G'|$ **then**
        $S' \leftarrow G'$
    else
        $S' \leftarrow G$
    end
    return S'
end procedure

avoids to choose redundant samples, and rather, choose those less expensive which maximize the coverage. Furthermore, in order to increase the geographical coverage balance and encourage the mobility towards areas that have not been covered previously.

C. participant recruitment mechanisms

We use the recurrent Reverse Auction Based Dynamic Price with Virtual Participation Credit and Recruitment (RADP-VPC-RC) presented by [14] as the recruitment mechanism. RADP-VPC-RC works using rounds, thus, at every round t participants offer to sell their sensing samples to the platform. We use RADP-VPC-RC in combination with our greedy algorithm, and our geometric sensing model to acquire the set of samples that cover the space using spheres at minimum cost.

Flowchart in Figure 4 sketches the main components of our recruitment approach. Flowchart input include participant true valuation (t_v) or minimum value a participant is willing to accept for its sample, t_v is generated from normal distribution. Other inputs are current round (r), the total number of participants n, the number of winners m, and α and β which corresponds to parameters of return of investment (ROI) or S_i. Vehicles' bid's price is randomly generated from an uniform distribution from $[t_v, 1.5t_v]$ which corresponds to the t_v plus a small profit. The set of winner $S^{'}$ is computed using Algorithm 3 (Selecting Winners). The winners (yes, left arrow) increase their bids' price by 10% with a 50% probability. On the another hand, all the losers decrease their bids' price by 20% in the hope of winning in the next round. In addition, the losers bids' price is artificially decreased using the virtual participation credit VC. The losers also evaluate their return of investment (ROI) or S_i. If S_i ¡ S_{th} where S_{th} is a threshold, the participant drops, otherwise that vehicle will participate in the next round. Here, Equation 1, represents S_i.

$$S_i = \frac{e_i^r + \beta_i}{p_i^r.t_i + \beta_i} \tag{1}$$

Where, e_i^r corresponds to the earned reward by user i until round r. $p_i^r.t_i$, corresponds to the minimum reward, with p_i^r as the number of participation instances of i up to the current auction round r. For those who drop the system uses a re-join mechanism, which allows the auctioneer to communicate the maximum winning price φ_k to the users that dropped out of the system. The knowledge of this price allows the users to re-evaluate their ES_k^{r+1} and potentially return to the next auction round. This expected ES_k^{r+1} is evaluated in Equation 2

$$ES_i = \frac{e_k^r + \varphi_k + \beta_k}{(p_k^r + 1).t_k + \beta_k} \tag{2}$$

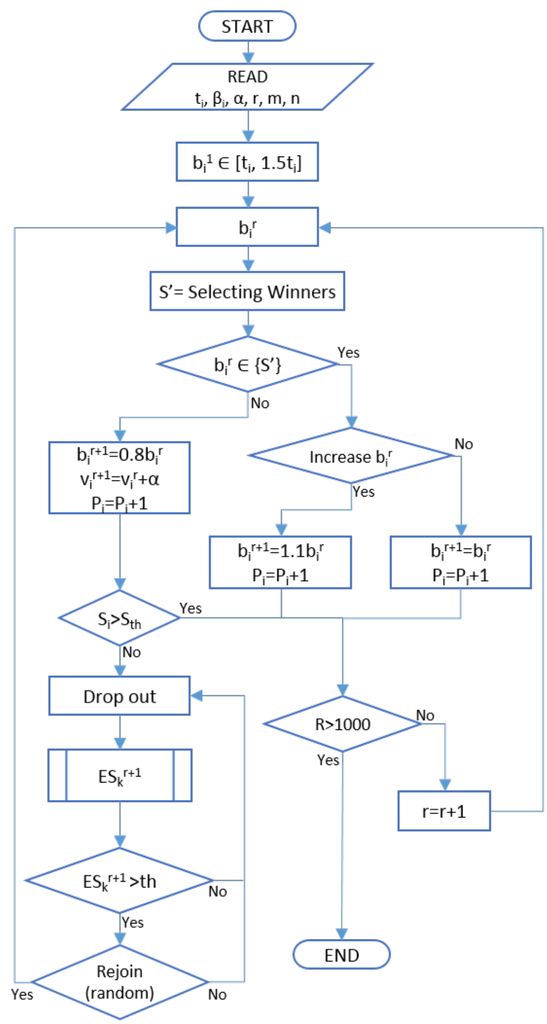

Fig. 4: Participant Recruitment Mechanisms (PRM)

IV. Performance Evaluation

We evaluate two important metrics for VCS, namely percentage of area coverage and number of active participants.

Area coverage is improved by using the geometric model, and active number participants (ANP) is tackled by the recruiting framework. ANP is a fundamental element in crowdsensing, in particular for systems based on recurrent reverse auctions. Here, participants who are not able to continuously sell their samples find that the cost of participation is greater than the reward that result from selling samples . Thus, these rational participants will drop from the system causing that few survivors increase their bid's price in an exponential way, this as result of the lack of competition. We address this problem by using a virtual participation credit (aging approach) and a re-join model that encourage drooped participants to reconsider participation.

We evaluate the efficiency of the incentive model implemented as a SUMO scenario. To improve the performance of our VCS model, we used a DSN generated using Goss *et al.* [7] technique in place of an OSM SN. The model contains realistic data mapping to the common vehicle behaviors retrieved from the Uber Movement dataset [20] and applied to the roads in the SN. Each simulation step represents a single round in the algorithm, after each round, we capture the active participants and compute the coverage ratio through the use of Monte Carlo simulation. The result of this approach is compared to the minimum cost approach, where the samples were chosen starting from the lowest bid prices until the budget runs out.

A. Experimental Setup

We perform the experiments as follows. The participants are initialized with a random starting location and ending location following a 2-dimensional uniform distribution. Prior to starting the first round, all the participants are assigned their true valuations, and bid prices generated using a normal distribution with the parameter shown in Table 1. The first round starts as the participants begin to travel towards their destination following the shortest path determined by Dijkstra's algorithm. The winners are chosen during the round are represented using disks with the predetermined R value Figure 5, our goal is for these disks to have minimum overlap with maximum coverage, at the same time staying within the budget constraints. The coverage area are computed using Monte Carlo simulation following the flow shown in Figure 6. T denotes the counter for the total number of points generated and C denotes the number of points that are covered by the disks. Random points P are generated uniformly between the boundaries of the map, and euclidean distance is used to determine whether the point falls within the radius of any given disks. The coverage percentage is computed by $\frac{C}{T}$. Experiment parameters are presented in Table I

B. Experiment 1 (Average Coverage Percentage)

In order to study the relationship between budget and coverage, we change the value for budget from 5 to 50 with increments of 5 while keeping all other variables constant. For each budget value we repeat the simulation 1000 times and the results are averaged. Figure 7 shows the average coverage for each budget value, the graph shows when the budget value is low, the incentive mechanism seems to have worse performance, however this is only due to the randomness for both algorithms when the budget is really low. As the budget increase we see a significant improvement in performance for our incentive mechanism, it out performs the greedy approach by IMVCBC as the budget approaches 50.

TABLE I: Simulation Parameters

Parameter	Value
Target Area	5200 x 5200 meters
# Edges	9119
True Valuation	
μ	5
σ	2
Monte Carlo Simulation	100000
Number of Vehicles	100
Source	random
Destination	random
Budget	
IMVCBC	range(start=5,end=50,step=5)
Greedy	range(start=5,end=50,step=5)

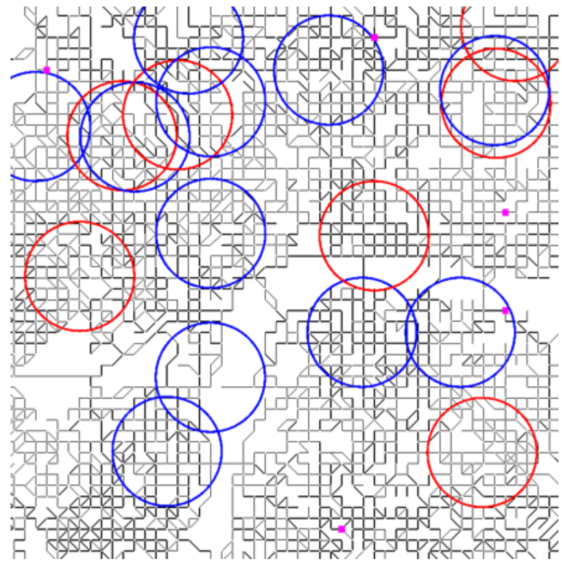

Fig. 5: Single round result IMVCBC (blue) vs greedy bid (red)

C. Experiment 2 (Active Participants)

The experiment for active participants follows the same setup as the experiment for coverage percentage. Each round the number of participants that are actively participating in the auction is captured, Figure 8 shows the relationship between budget and the average number of participants that participates in the auction over the 1000 rounds of simulation, the graph shares a similar behavior as the experiment for coverage, the growth for the greedy algorithm is slow and steady while our incentive mechanism shows a much better rate of growth as the budget value increases.

V. Acknowledgements

This material is based upon work partially supported by the National Science Foundation (NSF) under NSF Award

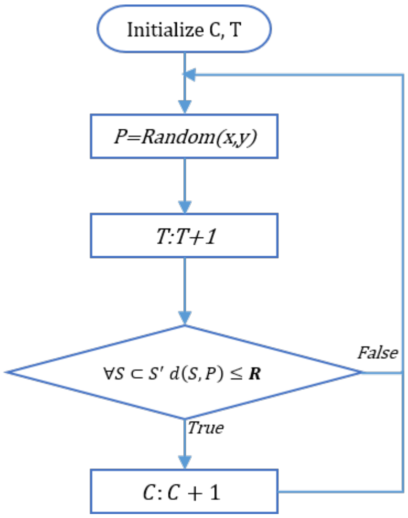

Fig. 6: Monte Carlo area estimation

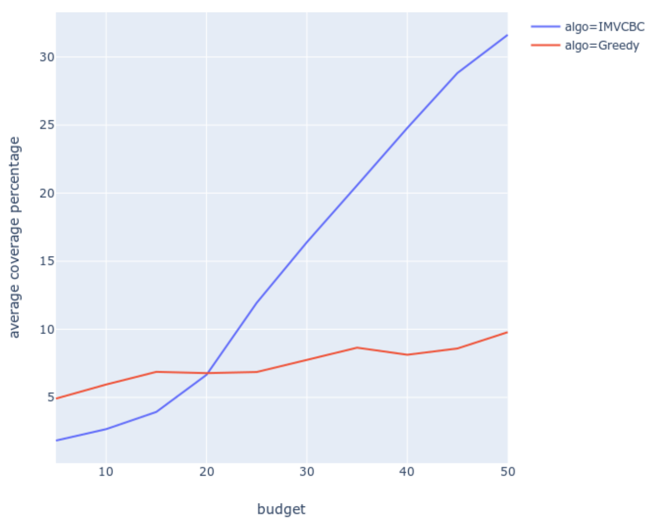

Fig. 7: Budget value vs. Coverage

Number 1739409. Any opinions, findings and conclusions, or recommendations expressed in this material are those of the author(s), and do not necessarily reflect those of the NSF.

The street network data is partially derived from OSM data ©OSM contributors and available at www.openstreetmap.org/.

Data retrieved from Uber Movement, (c) 2020 Uber Technologies, Inc., https://movement.uber.com.

VI. Conclusion and Future Work

This paper presents Incentive Mechanism for Vehicular Crowdsensing with Budget Constrains (IMVCBC). IMVCBC combines a geometric coverage model with a recruitment mechanism based on reverse action to encourage participant vehicles to collect sensing data. The use IMVCBC improves sensing coverage, reduce the collection of redundant data by while using a limited budget. Through the use of a real-world traffic model (SUMO) and extensive simulations, we test IMVCBC in terms of area coverage, and number of active participants. We found that IMVCBC outperforms a greedy policy by increasing area coverage by around three times, and number of active participants by eighth times.

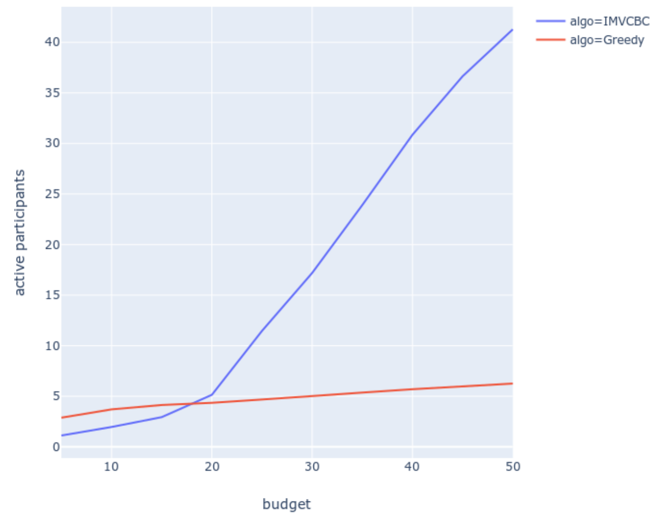

Fig. 8: Budget value vs. Active participants

References

[1] Mathieu Barbier, Christian Laugier, Olivier Simonin, and Javier Ibañez-Guzmán. Functional discretization of space using gaussian processes for road intersection crossing. In *IEEE 19th International Conference on Intelligent Transportation Systems (ITSC)*, pages 156–162, 2016.

[2] Geoff Boeing. Osmnx: New methods for acquiring, constructing, analyzing, and visualizing complex street networks. *Computers Environment and Urban Systems*, 65:126–139, 07 2017.

[3] Yueyue Chen, Pin Lv, Deke Guo, Tongqing Zhou, and Ming Xu. Trajectory segment selection with limited budget in mobile crowd sensing. *Pervasive and Mobile Computing*, 40:123–138, 2017.

[4] Amr S El-Wakeel, Jin Li, Aboelmagd Noureldin, Hossam S Hassanein, and Nizar Zorba. Towards a practical crowdsensing system for road surface conditions monitoring. *IEEE Internet of Things Journal*, 5(6):4672–4685, 2018.

[5] Niclas Evestedt, Erik Ward, John Folkesson, and Daniel Axehill. Interaction aware trajectory planning for merge scenarios in congested traffic situations. In *IEEE International Conference on Intelligent Transportation Systems (ITSC)*, pages 465–472, 2016.

[6] C. Fiandrino, A. Capponi, G. Cacciatore, D. Kliazovich, U. Sorger, P. Bouvry, B. Kantarci, F. Granelli, and S. Giordano. Crowdsensim: a simulation platform for mobile crowdsensing in realistic urban environments. *IEEE Access*, 5:3490–3503, 2017.

[7] Quentin Goss, Mustafa İlhan Akbaş, Alireza Chakerim, Xin Wang, and Luis G. Jaimes. Gdtsn: Grid discretization technique for street networks. *IEEE International Conference on Communications (ICC)*, submitted for publication.

[8] Kang Han, Cailian Chen, Qianli Zhao, and Xinping Guan. Trajectory-based node selection scheme in vehicular crowdsensing. In *2015 IEEE/CIC International Conference on Communications in China (ICCC)*, pages 1–6. IEEE, 2015.

[9] Zongjian He, Jiannong Cao, and Xuefeng Liu. High quality participant recruitment in vehicle-based crowdsourcing using predictable mobility. In *2015 IEEE Conference on Computer Communications (INFOCOM)*, pages 2542–2550. IEEE, 2015.

[10] Luis G Jaimes, Idalides Vergara-Laurens, and Miguel A Labrador. A location-based incentive mechanism for participatory sensing systems with budget constraints. In *2012 IEEE International Conference on Pervasive Computing and Communications*, pages 103–108. IEEE, 2012.
[11] Samir Khuller, Anna Moss, and Joseph Seffi Naor. The budgeted maximum coverage problem. *Information processing letters*, 70(1):39–45, 1999.
[12] Kaiwei Kong, Jian Xu, Ming Xu, Liming Tu, Yang Wu, and Zhi Chen. Trajectory query based on trajectory segments with activities. In *Proceedings of the 3rd ACM SIGSPATIAL Workshop on Smart Cities and Urban Analytics*, page 2. ACM, 2017.
[13] Daniel Krajzewicz, Jakob Erdmann, Michael Behrisch, and Laura Bieker. Recent development and applications of SUMO - Simulation of Urban MObility. *International Journal On Advances in Systems and Measurements*, 5(3&4):128–138, December 2012.
[14] Juong-Sik Lee and Baik Hoh. Dynamic pricing incentive for participatory sensing. *Pervasive and Mobile Computing*, 6(6):693–708, 2010.
[15] Nicolas Maisonneuve, Matthias Stevens, Maria E Niessen, and Luc Steels. Noisetube: Measuring and mapping noise pollution with mobile phones. In *Information technologies in environmental engineering*, pages 215–228. Springer, 2009.
[16] OpenStreetMap contributors. Planet dump retrieved from https://planet.osm.org . https://www.openstreetmap.org , 2017.
[17] Francesco Restuccia, Sajal K Das, and Jamie Payton. Incentive mechanisms for participatory sensing: Survey and research challenges. *ACM Transactions on Sensor Networks (TOSN)*, 12(2):13, 2016.
[18] Shuja Jamil Sheikh, Anas Basalamah, Heba Aly, and Moustafa Youssef. Demonstrating map++: A crowd-sensing system for automatic map semantics identification. In *Annual International Conference on Sensing, Communication, and Networking (SECON)*, pages 152–154. IEEE, 2014.
[19] Danyang Tian, Guoyuan Wu, Peng Hao, Kanok Boriboonsomsin, and Matthew J Barth. Connected vehicle-based lane selection assistance application. *IEEE Transactions on Intelligent Transportation Systems*, 2018.
[20] Uber Technologies Inc., 2019. Uber Mobility speed data for London, UK.
[21] S. Uppoor and M. Fiore. Large-scale urban vehicular mobility for networking research. In *IEEE Vehicular Networking Conference (VNC)*, pages 62–69, Nov 2011.
[22] P. Vitello, A. Capponi, C. Fiandrino, P. Giaccone, D. Kliazovich, and P. Bouvry. High-precision design of pedestrian mobility for smart city simulators. In *IEEE International Conference on Communications (ICC)*, pages 1–6, May 2018.
[23] Cheng Wang, Zhenzhen Zhang, Lu Shao, and MengChu Zhou. Estimating travel speed via sparse vehicular crowdsensing data. In *3rd World Forum on Internet of Things (WF-IoT)*, pages 643–648. IEEE, 2016.
[24] Leye Wang, Daqing Zhang, Yasha Wang, Chao Chen, Xiao Han, and Abdallah M'hamed. Sparse mobile crowdsensing: challenges and opportunities. *IEEE Communications Magazine*, 54(7):161–167, 2016.
[25] Axel Wegener, MichałPiórkowski, Maxim Raya, Horst Hellbrück, Stefan Fischer, and Jean-Pierre Hubaux. Traci: An interface for coupling road traffic and network simulators. In *Proceedings of the Communications and Networking Simulation Symposium*, pages 155–163. ACM, 2008.
[26] Liang Xiao, Tianhua Chen, Caixia Xie, Huaiyu Dai, and H Vincent Poor. Mobile crowdsensing games in vehicular networks. *IEEE Transactions on Vehicular Technology*, 67(2):1535–1545, 2018.
[27] Susu Xu, Xinlei Chen, Xidong Pi, Carlee Joe-Wong, Pei Zhang, and Hae Young Noh. Incentivizing vehicular crowdsensing system for large scale smart city applications. In *Sensors and Smart Structures Technologies for Civil, Mechanical, and Aerospace Systems 2019*, volume 10970, page 109701C. International Society for Optics and Photonics, 2019.
[28] Xiru Zhu, Shabir Abdul Samadh, and Tzu-Yang Yu. Large scale active vehicular crowdsensing. In *IEEE Vehicular Technology Conference VTC*, pages 1–5. IEEE, 2018.