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Highway Roadside Unit Deployment Schemes based on Empirical Mobility Traces

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Abstract: Intelligent Transportation Systems (ITS) will rely on information exchange among vehicles and infrastructure to deliver an efficient and comfortable mode of travelling. One of the most critical components of an ITS is the presence of roadside units (RSUs) for storage, computation and data processing. In this work, deployment schemes are presented to determine which part of a highway can be considered as a candidate location by employing empirical vehicular mobility traces. Results show that a simplistic approach can readily determine these possible locations at the fastest runtime, while achieving maximum coverage and connectivity among vehicles and infrastructure.

Key Words: Roadside Unit Deployment Schemes; Empirical Mobility Traces; Highway Setup

1. INTRODUCTION

As more vehicles ply the city streets and roads, an increase in travel inconvenience is seen in terms of traffic, travel time, CO_2 emission, and route planning. Vehicles will heavily rely on real-time road data captured and shared by vehicles. However, these environment data have huge file size that makes it harder to disseminate. One practical way to overcome this limitation is the deployment of roadside units (RSUs) at strategic locations. Lochert (Lochert C. , Scheuermann, Caliskan, & Mauve, 2007) proposed the use of stationary supporting units (SSUs) to aid vehicles in information dissemination in vehicular networks. The SSUs were manually positioned in three locations, namely (1) market places, (2) high traffic density areas and (3) random distribution. Later, they used genetic algorithm to identify the good position where roadside units (RSUs) must be placed (Lochert C. , Scheuermann, Wewetzer, Luebke, & Mauve, 2008). Assuming that RSUs are networked, both researches were able to prove that these infrastructures, even small in number, provide a higher probability for vehicles to receive up-to-date information. (Sou & Tonguz, 2011) analyzed the improvement in terms of vehicular network connectivity even when a limited number of RSUs were deployed. An optimal placement and configuration of RSUs were formulated in (Liang, Liu, & Rajan, 2012) as an integer linear program based on power level, antenna type and wired/wireless network connectivity. For a low-density vehicular network, (Abdrabou & Zhuang, 2011) provided an analytical framework to estimate the minimum requirement of RSUs to be deployed to cover a road segment. Mobility traces used were synthetically or analytically generated from traffic simulators or an exponential distribution. Efficient data dissemination approaches are seen in (Ali, Chong, Samantha, & Chan, 2016) using cooperative multi-RSUs and in (Chau, Ho, Magsino, & Jia, 2016) employing opportunistic scheduling. Both papers assume that the RSUs are already deployed in the urban setup.

Studies in wireless sensor networks (WSNs) have abundant research work related to the optimal deployment of sensor nodes (Bojkovic & Bakmaz, 2008). However, according to (Wang, Lim, & Ma, 2009), random deployment of sensor nodes in WSNs results to a number that is usually more than the necessary, thus, we exclude this from our approach. Also, such random deployment cannot also be introduced to vehicular networks since the road network is very much deterministic and fixed in topology.

Unlike WSNs, vehicular networks do not suffer from lifetime limitations since it is assumed to be connected to a power grid, thereby placing an RSU in standby mode is not recommended. It is either turned ON or OFF. The main problem lies in the connectivity and coverage between vehicles and infrastructure and the abundance of sensed environment data needed to be shared.

In this study, we explore how to determine candidate RSU locations in a highway setup using empirical mobility traces, while maintaining full coverage and connectivity of the vehicles with the infrastructure. The results can later be used for information exchange (Chu, Magsino, Ho, & Chau, 2017).

The paper is organized as follows. Section 2 discusses the five deployment schemes for determining the candidate RSU locations. Section 3 presents the simulation results and provides some discussions. Finally, Section 4 concludes the work presented and lays out future direction of the research.

2. METHODOLOGY

This section discusses the various methods on how to obtain candidate RSU locations given a highway setup. The candidate RSU deployment schemes determine RSU locations for maximum coverage and connectivity while using the least possible number of RSUs. The minimum number of deployed RSUs is obtained by following the general problem definition that at all desired sampling times, a vehicle is within range to at least one RSU, signifying that there is a total (maximum) coverage of a certain urban setup. Such is called the *online* case scenario, since at any time, a vehicle can communicate with an RSU for any data transmission/exchange or emergency inquiry. This real-time connectivity offers the advantage of knowing the traffic/environment conditions at any time and all possible locations with vehicles simultaneously.

2.1 Simplistic Approach

The method divides the highway into $r \times c$ partitions, where the number of partitions, rc, is dependent on the transmission range of the RSU. Small overlapping between RSUs especially at the RSU's transmission boundaries can provide connectivity when vehicles leave a certain RSU area and enter another location. Once the highway is modeled into an $r \times c$ matrix, each row-column combination is checked for presence of a vehicle's GPS trace. Once the matrix elements are completed, candidate locations with values less than a threshold is removed, thus, leaving the list of possible candidate RSU locations.

2.2 Diminishing Grid Point Method

This scheme determines the histogram of vehicles in each partition. Choosing candidate RSU locations starts from the spot with the highest vehicular density. Once a location is already chosen, all grid points within the transmission range are removed, and the next grid point with the highest vehicular density is chosen. The process is iterative until no more grid points are left.

2.3 Iterative K-means Method

The K-means clustering algorithm groups the given dataset into K number of groups by satisfying a certain set of criteria (Hartigan & Wong, 1979). In this work, the Euclidean distance is chosen to group the vehicular GPS traces. The value of K is determined once all GPS traces are already included in all chosen candidate RSU locations. A faster k-means algorithm using matrix operations is implemented (Cai, 2019)

2.4 Grid-Growing Method

The Grid Growing Method (Zhao, Shi, Liu, & Fränti, 2015) is designed for geo-spatial data like vehicular traces. It creates an $n \times n$ grid structure and assign each GPS trace to a certain grid according to its location. Based on the given number of starting seeds (clusters), the grid is grown to cover all vehicular traces.

2.5 DRO-DBSCAN Method

The clustering method of Density-Based Spatial Clustering of Applications with Noise (DBSCAN) is based on reachability and connectivity of points. If certain points are not grouped, DBSCAN considers them as outliers or noise. We modify the DBSCAN algorithm such that the density reachability criterion is only (DRO) used. Reachability is defined as points within a neighborhood of the other points and is dependent on the RSU transmission range.

3. RESULTS AND DISCUSSION

In comparing the various candidate RSU deployment schemes, we use the empirical traces of Beijing taxis utilized in (Magsino & Ho, Roadside Unit Allocation for Fog-based Information Sharing in Vehicular Networks, 2018). It is a dataset containing the mobility traces of approximately 28,000 taxis plying the streets of Beijing for seven days. Each location is sampled every 10 seconds. These GPS traces are analyzed first if there are any days that are outliers, e.g., holidays, special event, etc. As for the highway setup, the *East Rd 3rd Ring* spanning an area of 9 km (highway length) by 2 km (highway width) is considered.

Fig. 1 illustrates the fact that there are no discrepancies in each day in determining the number of candidate RSU locations (using the Simplistic Method) when the sampling time has been changed.

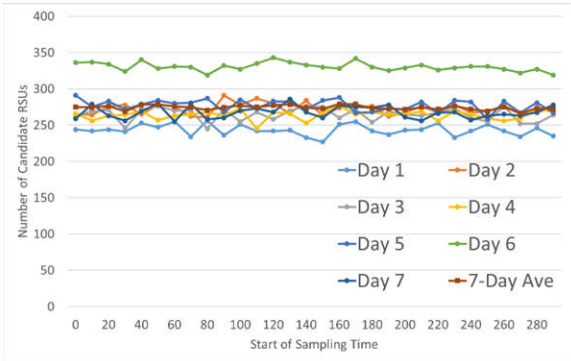

Fig. 1. Daily number of candidate RSU locations having variable sampling time.

Note that as the sampling time is increased, the number of available taxi traces is not reduced. This implies that there is no decrease/reduction on the number of available taxis, therefore, to reduce simulation time, we can select sampling time that has low granularity, i.e., higher sampling time. A higher sampling time greatly reduces the number of the GPS traces to be analyzed. Day 6 taxi traces provide the greatest number of possible candidate RSU locations, due to the fact that there are more scattered taxi GPS locations compared to the other six days have almost the same response. In addition, the dataset does not contain any information regarding what event there is on Day 6.

Fig. 2 depicts the average number of candidate RSU locations for each RSU transmission range as computed by each deployment scheme. The best (the lowest number of deployed RSUs) deployment scheme is the Simplistic while the worst (most number of deployed RSUs) is the Grid-growing technique. It is also obvious that increasing the transmission range from 100 meters to 200 meters reduced the needed RSUs by half. As the transmission range is increased to 500 meters, except for the Grid-growing method, the required number of RSUs needed for monitoring vehicles is almost the same for the four methods. The Diminishing Grid Point and DRO-DBSCAN methods have the same number of calculated candidate RSU locations. This is the result of only using the density reachability criterion of DBSCAN. DRO-DBSCAN reduces to the Diminishing Grid Point method.

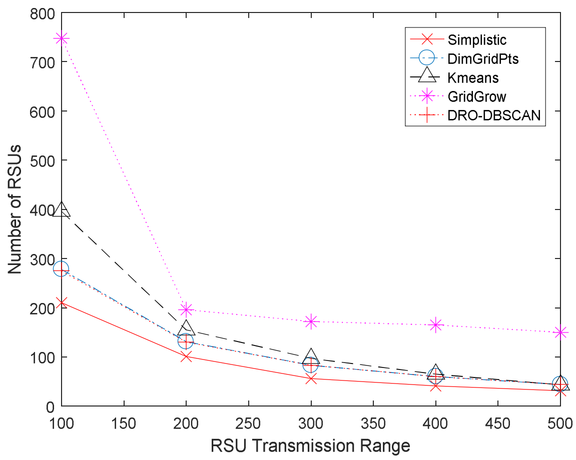

Fig. 2. The average number of candidate RSU locations computed by each deployment scheme while varying the RSU transmission range (in meters).

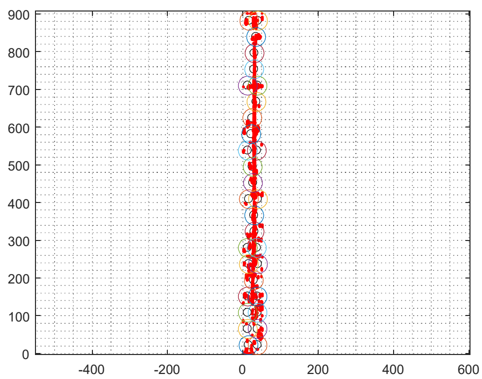

Fig. 3. The deployment of candidate RSU locations using the Simplistic Approach having an RSU transmission range of 500 meters.

Given these findings, highways can reduce traffic jams on entry/exit ramps and efficiently create a smooth traffic at the tollgates employing computational intelligence to equalize tollgate utilization and reduce waiting time among vehicles (Magsino & Ho, An intelligent highway tollgate queue selector for improving server utilization and vehicle waiting time, 2016). A sample candidate RSU deployment locations utilizing the Simplistic Approach and RSU transmission range of 500 meters is shown in Fig. 3. For highway sections with only one circle, it represents the highway part with no entry/exit ramps, as compared to those parts with two circles. Red dots are the average GPS locations of vehicles for seven days.

Table 1 summarizes the average runtime of each method given a sampling time of 15 minutes of the taxi mobility traces. The Simplistic Approach still outperforms the rest of the deployment schemes. Iterative K-means performed the worst and is expected. Even though the Diminishing Grid Point and DRO-DBSCAN have the same number of candidate RSU locations, DRO-DBSCAN runs at a much faster time. This is due to the fact that the Diminishing Grid Point re-arranges the remaining grids according to the highest number of vehicles present in a grid but is not the case in DRO-DBSCAN.

Table 1. Summary of Average Runtimes

Deployment Method	Runtime (in sec)
Simplistic	0.1179
Diminishing Grid Point	3.1459
Iterative K-means	25.1934
Grid-growing	0.7690
DRO-DBSCAN	0.3858

4. CONCLUSION

In this work, five deployment schemes for determining the candidate RSU locations on a highway setup are presented. Among these, the Simplistic Approach is the best method since it provides the least number of needed RSUs for monitoring highway vehicles and determines it by consuming the least amount of time. Each scheme satisfies the objective of maximum coverage and connectivity of vehicles to a roadside infrastructure.

Since RSUs are generally costly, optimal deployment from these candidate locations becomes the focus of the next research. We deal mainly in the data dissemination of road map data among vehicles and RSUs. This will enable intelligent vehicles to maneuver roads easily and avoid accidents.

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