XXX Vehicle-based Crowd Sensing with Schedulable Trajectory XXX

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***Abstract*—Mobile crowd sensing has been becoming a prospective paradigm with smartphone, which can collect ubiquitous data easily in large-scale city. Nowadays, public transport buses are mostly widely used and affordable transport vehicle in many urban. A buses embedded with substantial sensors also can be adopted as participator in crowd sensing. However, distinct from smartphones, the trajectory of bus is scheduled and whose location is predicted, which opens up a new opportunities to achieve high quality crowd sensing. A high quality of a crowd sensing network highly depends on the spatial-temporal coverage of sensing data, therefore, based on the predictable trajectory of vehicles, we design a novel model and present an approximation algorithm to select vehicles to participate in urban sensing for maximizing spatiotemporal coverage with constraint sensing reward. We theoretically prove that the selection of vehicles problem is NP-hard, the proposed algorithm can achieve a performance guarantee no less than $\left(1-e^{-1}\right)$ of theoretical optimum. The performance of our algorithm is stimulated with real T-Drive trajectory dataset. The results shows that our algorithm achieves a good coverage closer to optimum and outperform some exiting alternative algorithms.**

***Index Terms*—Mobile crowd sensing, spatial temporal coverage, approximation algorithm, performance guarantee.**

I. Introduction

WITH the rapid advance of sensing, communication, and mobile computing, mobile crowd-sensing [1] has become a paradigm attached much attention for gathering distribute sensory data to share with the general public. With the help of mobile crowd-sensing the cost of many data collection and dissemination tasks over wide range of region can be significantly reduced. Being carried by human user who locate in different place, smartphone can easily collect ubiquitous data and share such data with a large number of potential users [2], [3]. The vehicle-based mobile crowd-sensing with similar mobility, distribution in large is evolving rapidly. Equipped with onboard sensors such as GPS, video cameras and communication module and so on, a vehicle also can become a powerful crowd-sensing application like as a smartphone to collect data and execute a various of sensing task, including traffic monitoring [4][5], environment monitoring [6],urban Wi-Fi characterization [7], etc. A vehicle-based mobile crowd-sensing system typically composed of two parts: cloud management platform (CMP) and mobile vehicles embedded with crowd sensing application. An example of vehicle-based crowd sensing is shown in Fig.1. The cloud management platform is responsible for selecting a set of vehicles to participate in urban crowd sensing task and processing perceives data which forwarded from vehicles to provide data services to user. Once a vehicle receives authorization of CMP, it will gather the required data and then upload to CMP. This indicates that a is capable of supporting a wide range of large-scale monitoring [8]. Generally, it is greatly important to select vehicles to participate in collaborative sensing, which manifest the success of vehicle-based mobile crowd sensing. Consider an extreme case that the CMP select all vehicles to execute crowd sensing task, apparently, it can perceive the surroundings and achieve what it is assigned to do, but multiple vehicles in the same region at the same time will introduce data redundancy due to a single vehicle is sufficient to cover a geographical region, which application should avoid. Therefore, the vehicle usually receive credit or non-monetary reward from CMP [9]-[11] with constraint budget, and selects a set of vehicle from all vehicles under operation that best satisfy with the users requirements for better crowd sensing quality[11].

The location of vehicles make a greatly influence on the quality of vehicle-based mobile crowd sensing [12], because of the CMP assigns tasks to vehicles that operates in different regions. As mentioned above, vehicles within same region introduces redundancy, this case is we try to avoid. There is another worst case where no vehicles are operating in the regions of interest at a specific time resulting in blank data. Obviously, the quality of crowd sensing is sensitive to space and time, so the spatial-temporal coverage is a fundamental metric of the vehicle-based mobile crowd sensing quality. Particularly, spatial-temporal coverage intends to cover as many regions of interest as possible and make sure all areas is covered at least once for a period of time. In reality, we are supposed to be aware that the spatial-temporal coverage of sensing data of vehicle-based mobile crowd sensing is more dynamic on account of each vehicle keeps moving persistently across the city as his own schedule. However, public transport buses, which is distinct from taxi or private car without operating plans, strictly periodically follow an explicit timetable made by bus company. Hence the location of each bus is predictable in spite of the highly dynamic mobility, which opens up a new opportunities to achieve high quality crowd sensing. Because each bus is able to cover many areas for a period of time. For another, taking into consideration the future location of vehicles can effective prevent the quality of crowd-sensing from affecting for high mobility instead of only depend on current location as smartphone-based crowd-sensing do[13]. In the next, a vehicle refer more politically to be a bus.

In this paper, we concentrate on how to achieve a high

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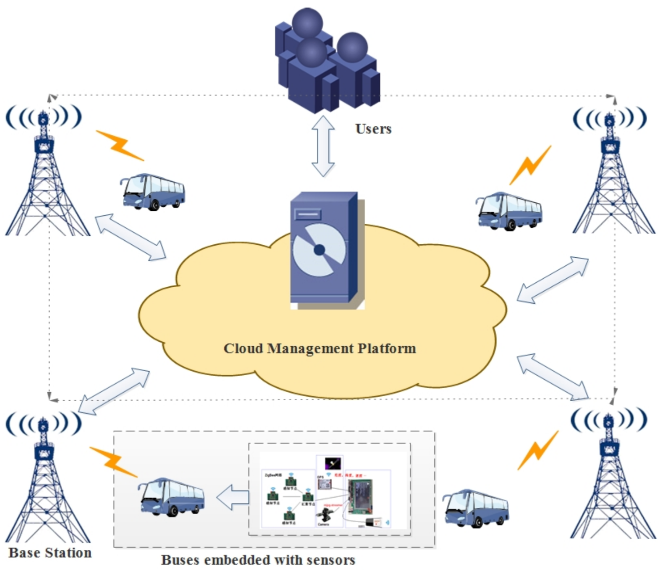

Fig. 1. An example of vehicle-based crowd sensing application. Buses embedded with plentiful sensors are distributed over a large city. Cloud management platform assign sensing task to the recruited vehicle which can contribute to the sensing tasks by returning their sensed data to CMP. And then CMP processes the received data to provide to user.

quality of crowd sensing making full use of the predictable location of buses. After an analysis on the relations between spatial-temporal coverage and the location of vehicle, we formulate the problem of selection vehicle (SV) for maximizing the spatial-temporal coverage of city with constraint budget. Through thoroughly proof, we find that SV is NP-hard. And we design a truthful and efficient approximation algorithm, called ECQA, to select a set of vehicle from all candidates under operation with a high efficiency (minimal budget and maximizing spatial-temporal coverage), which can approximate the optimal solution within a guarantee performance no less than $\left(1-e^{-1}\right)$, with polynomial-time computation complexity. We also theoretically prove the ECQA guarantee is truthfulness.

II. System Model and Problem Formulation

A. System Model

We consider a vehicle-based crowd sensing system consisting of a CMP and many vehicles embedded with substantial sensors. The CMP periodically propagates sensing tasks to be completed by running vehicle. In a city area, we divide road into a serial of small segments. As an example shows in figure 2. Let R denote the set of all small segments, $R = \{r_1, r_2, r_3, ..., r_k\}$. When the CMP broadcasts a crowd-sensing task to be finished for a period of time, i.e. T. Supposed the time is discrete, so we can assume $T = \{t_1, t_2, t_3, ..., t_m\}$.The distribution of vehicle is large-scale, each vehicle equipped with the sensor module that we has designed in [14] is able to join crowd-sensing tasks. Assume there are n vehicles can perform sensing assignments and the set of vehicles is denoted by $V = \{v_1, v_2, v_3, ..., v_n\}$. Initially, the CMP predicts the current position of all vehicles according to the timetable and broadcast the data packet until receive the ACK, if the prediction is not consistent with the actual current location obtained through Global Positioning System (GPS) [15] employed in vehicle, it will be updated, respectively. With the initial location of vehicles and scheduled timetable, we can get the location of a vehicle v_i at a specific time t_j, which is denoted by . Thus the trajectory of n vehicles can be represented as follows:

$$L(V) = \begin{bmatrix} l_1(t_1) & l_1(t_2) & ... & l_1(t_m) \\ l_2(t_1) & l_2(t_2) & ... & l_2(t_m) \\ . & . & . & . \\ . & . & . & . \\ . & . & . & . \\ l_n(t_1) & l_n(t_2) & ... & l_n(t_m) \end{bmatrix} \tag{1}$$

where the size of $L(V)$ is $n \times m$.

In practice, we are not anticipate that all vehicles are involved in crowd sensing due to it will introduce redundancy. For example, in terms with traffic monitoring, nearby vehicles usual upload the same traffic information, which ought to avoid. Therefore, we regular that a vehicle who is selected to take part in crowd sensing will gain a reward paid by CMP and the budget of CMP is limited and no morn than C_{max}. Next, we define the sensing reward.

Definition 1: Sensing Reward (SR) a vehicle is selected to complete tasks often associated with a reward paid by CMP. Let c_i denote the reward to v_i, the reward can be acquired through online bidding [1]. Then, the reward vector C for all vehicles is:

$$\mathbf{C} = \{c_1, c_2, ..., c_n\} \tag{2}$$

With the constraint of budget of CMP, not all vehicles participate in crowd-sensing, we utilize an indication vector Φ to imply whether a vehicle v_i is selected or not

$$\Phi_i = \begin{cases} 1 & v_i \in \Omega \\ 0 & otherwise \end{cases} \tag{3}$$

where $\Omega \subseteq V$ is the set of selected vehicles. Let C be the total reward to buses in Ω, which can be computed as

$$C(\Omega) = [C, \Phi] \tag{4}$$

As mentioned, the quality of crowd sensing is related with spatial-temporal coverage, which means to cover as many regions of interest as possible and ensure each road segment to be covered once at least within a sensing time T. Let we introduce the notion of spatial-temporal coverage.

Definition 2: Spatial-temporal Coverage (STC) determines the quality of crowd-sensing. Formally, which can be defined as

$$\mathbf{STC} = \sum_{t_j \in T} \bigcup_{v_i \in \Omega} (l_i(t_j)) \tag{5}$$

Next, we show an example to explain the implication of STC. In Fig.2, the scheduled trajectory of Bus1, Bus2, Bus3, Bus4 is BC, AB, AD,DE , BC BE, EH, EH, HD, AD, AB, BE,EF, BE,AB, AD, DH, respectively. In a period time t_1, t_2, t_3, t_4 the location of Bus1 to Bus4 is BC, AD, DE, BC, BC, BE,

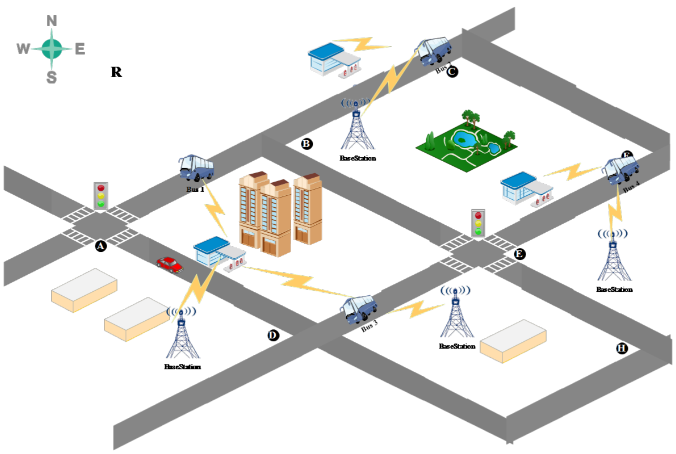

Fig. 2. An example shows that we divide the city area into small fragments, such as $R = \{AB, AD, BC, BE, DE, EF, EH, DH, CF\}$, where R is the city area.

BC,BE ,EH, HD, AB, BE, AB, BE, AD ,DH, respectively. From equality (1), we get

$$L(V) = \begin{bmatrix} BC & AD & DE & BC \\ BC & BE & BC & BE \\ AB & BE & AB & BE \\ AB & BE & AD & DH \end{bmatrix} \tag{6}$$

If the CMP with budget limited is capable of selecting two vehicles to participate crowd-sensing, then we consider two cases as bellows

$$\begin{aligned} STC(Bus1, Bus2) = & \underbrace{BC}_{t_1} + \underbrace{AD + BE}_{t_2} + \underbrace{DE + BC}_{t_3} \\ & + \underbrace{BC + BE}_{t_4} \end{aligned} \tag{7}$$

$$STC(Bus3, Bus4) = \underbrace{AB}_{t_1} + \underbrace{BE}_{t_2} + \underbrace{AB + AD}_{t_3} + \underbrace{BE}_{t_4} \tag{8}$$

It can be seen that the set of Bus1, Bus2 have covered five different place in space and the segment of BC has been covered triple over time. On the contrary, the set of Bus3, Bus4 simply have covered four different place in space, so we are more willing to select Bus1, Bus2 to participate in crowd sensing.

B. Problem Statement

In a region of interest, each vehicle equipped with amount of sensors which continuously sense the surrounding environment as it passes. However, at a specific moment, if all vehicles within a same road segment are involved in crowd-sensing, it will lead to overlap coverage. Thus it is highly demand to select an appropriate set to finish the crowd-sensing tasks and ensure the quality of crowd-sensing. Based on the system model, we are ready to formally define the problem of optimal selection of vehicle (SV) for maximizing the spatial-temporal coverage with SR budget constraint.

Definition 3: SV Problem (SVP)is to determine a set of vehicle under the budget constraint C_{max} with the objective of maximizing the spatial-temporal coverage.

$$\begin{aligned} & \textbf{max} STC(\Omega)) \\ & \textbf{s.t.} \quad C(\Omega) \leqslant C_{max} \end{aligned} \tag{9}$$

Actually, the sensing data at different road segment and at a different period time may have varying importance degree, such as we are more interested in hotspot with high traffic flow in the morning rush hour. For this reason, we introduce priority power to indicate the relative importance of each road segment where the higher priority a vehicle is more likely to be selected to join in crowd-sensing. Through analyzing historical data, it is easy to acquire traffic performance index (TPI) of each road segment. Let $D_{t_j}^{l_i}$ denote the TPI of $l_i(t_j)$ at a specific time t_j, which is assumed known and normalized between 0 and 1, e.g. $D_{t_j}^{l_i} \in (0, 1]$. With the TPI we define priority power.

Definition 4: Priority Power (PP) is the importance of a road segment in a crowd-sensing period time, which is a function of $D_{t_j}^{l_i}$ defined as $W_{t_j}^{l_i}(D_{t_j}^{l_i})$. So $D_{t_j}^{l_i} \propto W_{t_j}^{l_i}$, thus the first order derivative of $W_{t_j}^{l_i}(D_{t_j}^{l_i})$ satisfies

$$\frac{\mathrm{d}W_{t_j}^{l_i}}{\mathrm{d}D_{t_j}^{l_i}} > 0 \tag{10}$$

Therefore, priority power is expressed as follows

$$W_{t_j}^{l_i} = \log_2(1 + D_{t_j}^{l_i}) \tag{11}$$

With the priority power, the STC can be redefined as

$$\sigma(\Omega) = \sum_{t_j \in T} \bigcup_{v_i \in \Omega} (l_i(t_j) \cdot W_{t_j}^{l_i}) \tag{12}$$

so the SVP can be rewritten as

$$\begin{aligned} & \textbf{max} \ \sigma(\Omega) \\ & \textbf{s.t.} \quad C(\Omega) \leqslant C_{max} \end{aligned} \tag{13}$$

We hope that the solution of SVP can be found with a time efficient, unfortunately, it is NP-hard even though the trace of vehicles is predictable. In the next, we will prove SVP is NP-hard and propose an improved approximation algorithm based on greedy to solve it.

III. SOLUTION TO THE SVP

A. Complexity Analysis of SVP

Theorem 1. The SVP is NP-hard even though the trajectory of all vehicles are predictable. Proof: To prove the NP-hard property of SVP, we should demonstrate it belongs to NP firstly, and then find another NP-hard problem proven that could be reduced to it. Assuming there is a possible solution Ω', it is clearly that the correctness of this solution can be certified in polynomial, the time complexity of the checking algorithm is $O(n)$, which means SVP is NP. Next, we use an instance of budget maximum coverage problem as the known NP-hard, which is defined as follow. Given a collection of sets $S = \{S_1, S_2, ..., S_n\}$, each set $S_i \subseteq R = \{r_1, r_2, ..., r_m\}, i = 1, 2, 3..., n$ has a cost and an element $r_j, j = 1, 2, 3...m$ in R associated with a weight w_i.The question is whether we can find a subset $S^{'} \subseteq S$ that the total cost is not more than a given budge L and the total weight of elements in $S^{'}$ is maximized. Obviously, each set S_i can be mapped to $\sigma(Z), Z \subseteq V, c_i$ be equivalent to $C(Z)$, and weight w_i of each element in R is mapped to the priority power, $W_(t_j)^(l_i)$ of each vehicle in V. We have mapped the formulation of SVP to budget maximum coverage problem. And then we can see that a solution of budget maximum coverage problem is also the solution of SVP. So SVP is NP-hard.

Consequently, to achieve a truthful and computationally efficient crowd sensing system, it is highly demand to propose an approximate algorithm for solving SVP.

B. Approximate Algorithm to Solve SVP

We have analyzed the NP-hardness of SVP, it becomes computationally impracticable to select an optimal set of vehicles from all the candidate vehicles when the number of candidate vehicles is huge. As for a metropolis like Beijing, the number of vehicles under operations is about 30,000 by the end of 2016 [16]. To achieve the desired computational efficiency, we propose an approximate algorithm called efficient combination query algorithm (ECQA) to solve SVP. While designing the algorithm, not only should we consider to select a vehicle with maximized STC, but also ask for less reward from CMP with budget constraint. Therefore we define the reward efficient.

Definition 5: Reward Efficient (RE) indicates the marginal STC achieve per unit reward.

The ECQA adopts a greedy strategy to solve the problem. The greedy policy is to select the next most reward effectiveness vehicle, which means to select a vehicle maximized marginal STC per unit reward, until the total SR exceed the budget of CMP. Mathematically, the reward-efficient for selecting a vehicle v_i can be computed as follows

$$E_i = \frac{\sigma(\Omega^{'} - \sigma(\Omega))}{c_i} \tag{14}$$

The algorithm tries many rounds, a best vehicle with maximum RE is determined as a result of each round. In equation (14), where E_i denotes the reward efficient of vehicle v_i, is solution obtained from $V, \Omega^{'} = \{\Omega \cup v_i\}$ and $v_i \in V - \Omega$. The algorithm will not terminate until the budget constraint is active. The pseudo-code is listed in table 1.

The ECQA has a performance guarantee $\rho \leqslant 1$, which indicates we can obtain a solution is ρ times of optimal solution in NP-hard problem [17]. The closer of value of ρ to 1, the more approximation to optimal solution. In this paper, the ECQA can achieve a lower bound ratio of $\left(1 - e^{-1}\right)$ when the cardinality as q of set S^0 is not less than three, i.e. $q \geqslant 3$. Next, we will prove the following theorem about the performance guarantee of ECQA.

Theorem 2. The ECQA can achieve a worst performance guarantee of $\left(1 - e^{-1}\right)$ for $|q \geqslant 3|$.

$$\sigma(\Omega) \geqslant \left(1 - e^{-1}\right) \cdot \sigma(Opt), q \geqslant 3 \tag{15}$$

where Opt is the set in an optimal solution.

Proof: Lets redefine $v_i \in V, i = 1, 2, 3, ..., r$ as a vehicle added into Ω in i-th iteration, Let Ω_k denote $\bigcup_{i=1}^{k} v_i$, and $\Omega = \Omega_r$.

The pseudo-code of ECQA 1

Input: set $V = \{v_1, v_2, v_3, ..., v_n\}$ of vehicle under operation, set SC $= \{c_1, c_2, c_3, ..., c_n\}$ sensing reward of each vehicle, C_{max} the budget constraint of CMP, an initial set S^0 of cardinality is an integer as 3, assume the schedule time of each vehicle is known.

Output: set Ω is the best set of vehicle selected by ECQA.

```
max ← 0
Ω ← ∅
S ← ∅
for S^0 ⊆ V, C(S^0) ⩽ C_max do
    S ← S^0
    for v_i ∈ V − S do
        S' ← {S ∪ v_i}
        E_i ← (σ(S') − σ(S)) / c_i
        if E_i > max  and  C(S') < C_max then
            S ← S'
            max ← E_i
        end if
        if σ(S) > σ()Ω) then
            σ ← S
        end if
    end for
end for
```

To prove inequality (15), the following two inequalities we can derive from [18], After $i, i = 1, 2, 3, ..., r+1$ iterations, we can get

$$\sigma(\Omega_i) \geqslant \left[1 - \prod_{m=1}^{i}(1 - \frac{c_m}{C_{max}})\right] \cdot \sigma(Opt) \tag{16}$$

$$\begin{aligned} \sigma(\Omega_{r+1}) &\geqslant \left[1 - \prod_{m=1}^{r+1}(1 - \frac{c_m}{C_{max}})\right] \cdot \sigma(Opt) \\ &\geqslant \left[1 - \left(1 - \frac{1}{r+1}\right)^{r+1}\right] \cdot \sigma(Opt) \\ &\geqslant \left(1 - e^{-1}\right) \cdot \sigma(Opt) \end{aligned} \tag{17}$$

where c_m denotes the sensing reward to v_m. The detailed proof of inequalities (16), (17)can be found in [17],[18]. We can easily to know that (17) is equivalent to following inequality

$$\sigma(\Omega_{r+1}) = \sigma(\Omega_r) + \sigma(\{v_{r+1}\}) \geqslant \left(1 - e^{-1}\right) \cdot \sigma(Opt) \tag{18}$$

where v_{r+1} is selected at $r+1$ round but not added to Ω due to overflow budget constraint C_{max}. Applying (16) to (18), we get

$$\sigma(\Omega_r - S^0) + \sigma(\{v_{r+1}\}) \geqslant \left(1 - e^{-1}\right) \cdot \sigma(Opt - S^0) \tag{19}$$

where the set $Opt - S^0$ means that an element belongs to set Opt but not in set S^0.

Assuming $\sigma(\{v_{r+1}\})$ is greater than $\sigma(\{v_i\}), i = 1, 2, 3, ..., r$, if this were the case, v_{r+1} is bound to be selected before v_i and included in Ω_r, so this assumption is invalid. Therefore, we can get

$$q \cdot \sigma(\{v_{r+1}\}) \leqslant \sigma\left(S^0\right) \tag{20}$$

From (19), (20) the following inequality can be hold

$$\sigma(\Omega_r) \geqslant \left(1 - e^{-1}\right) \cdot \sigma(Opt - S^0) + (1 - q^{-1}) \cdot \sigma(S^0) \quad (21)$$

where e is a natural base whose value is less than three, hence

$$\sigma(\Omega_r) \geqslant \left(1 - e^{-1}\right) \cdot \left(\sigma(Opt - S^0) + \sigma(S^0)\right) \quad (22)$$

if and only if $q \geqslant 3$, the inequality (21) makes sense. Clearly, $\sigma(Opt - S^0) + \sigma(S^0) = \sigma(Opt)$, and then

$$\sigma(\Omega_r) \geqslant (1 - e^{-1}) \cdot (Opt), \ \ for\ q \geqslant 3 \quad (23)$$

Owing to the final output of ECQA as good as Ω_r if not better, this prove the performance guarantee of $(1 - e^{-1})$.

IV. EVALUATION

Extensive simulations has been conducted to evaluation the performance of our proposed algorithm. The traffic trace dataset we used, the simulation setup, the compared algorithms, and the performance comparison and discussion are presented as follows.

A. Real Traffic Trace Used and Simulation Setup

In our simulation, to make the evaluation results convincing, the T-Drive trajectory dataset [19], [20] that contains a one-week trajectory of 10,357 buses. The total number of points in this dataset is about 15 million and the total distance of the trajectories reaches 9 million kilometers. We have imported the processed data into the Google Global Mapper, as Fig.3 shows, the distribution of the trajectories of vehicles basically covers the whole traffic network of Beijing. Our simulation are performed on traces extracted from the dataset on February 3, 2008, 6 AM to 10 PM. We randomly extract a small number of vehicles from processed dataset to participate in crowd-sensing, i.e., 10, so that the optimal solution can be found though an enumeration algorithm. Each vehicle is associated with a SR, and the SR of a vehicle is uniformly distributed in [0.7, 1.2].

B. Algorithm in Comparison

The quality of crowd-sensing is related to STC, we evaluation how the total sensing reward C_{max}, the number of time period m, and the initial size of solution q impact on the performance. In this paper, we compare the performance of our algorithm with two baseline algorithm. 1) The enumerative algorithm (EA) can always get the optimal vehicles from the candidate vehicles by exhaustive search, however, the SVP is NP-hard, when the number of candidate vehicles is larger, it becomes infeasible to obtain the optimal solution in polynomial time. Thus, the EA is applied simply when the number of vehicles is small. 2) The simulated annealing algorithm (SAA) is often used to solve optimization problems, we improve a SAA to compute the SVP for maximizing the STC. Furthermore, the results are also compared with the lower bound performance guarantee STC $EA \cdot (1 - e^{-1})$.

Figs.4 illustrate the performance during the variation of the total sensing reward C_{max}, the number of period time m and the initial size of solution q. In this group of simulation, we

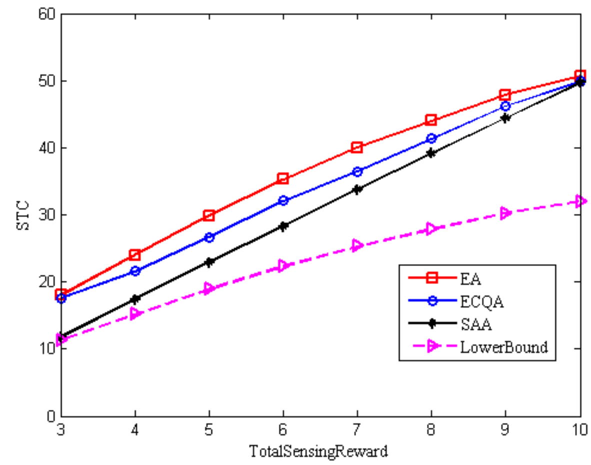

Fig. 3. The total sensing reward C_{max} is [3,10], the initial size of solution is 3, the number of period time is 6.

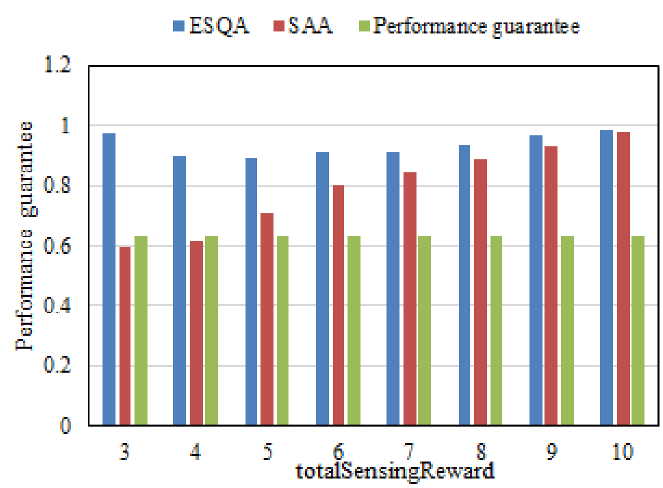

Fig. 4. The total sensing reward C_{max} is [3,10], the initial size of solution is 3, the number of period time is 6.

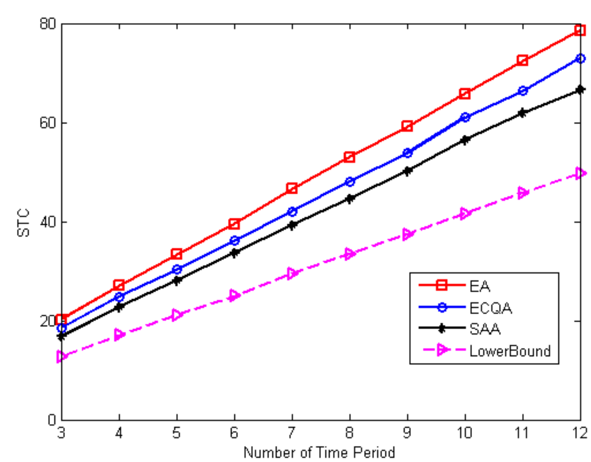

Fig. 5. The number of period is [4, 12], the total sensing reward C_{max} is 6, the initial size of solution is 3.

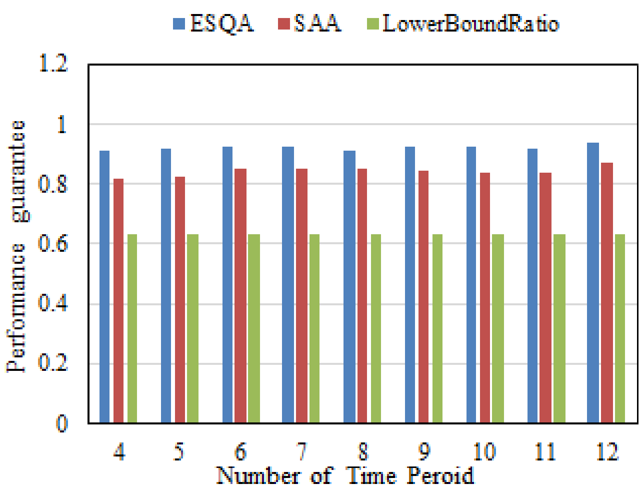

Fig. 6. The number of period is [4, 12], the total sensing reward C_{max} is 6, the initial size of solution is 3.

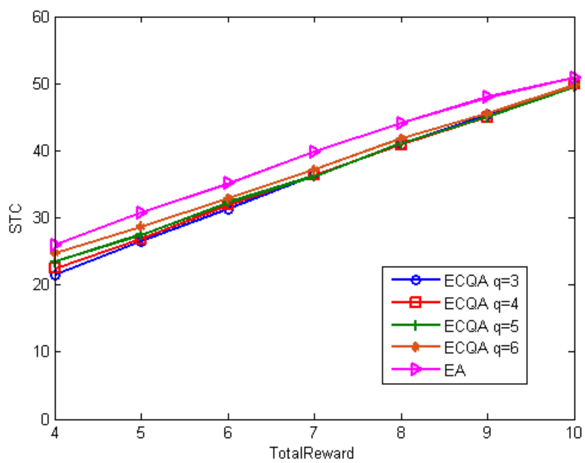

Fig. 7. The initial size of solution is [3, 6], the total sensing reward is [4, 10], the number of period time is 6.

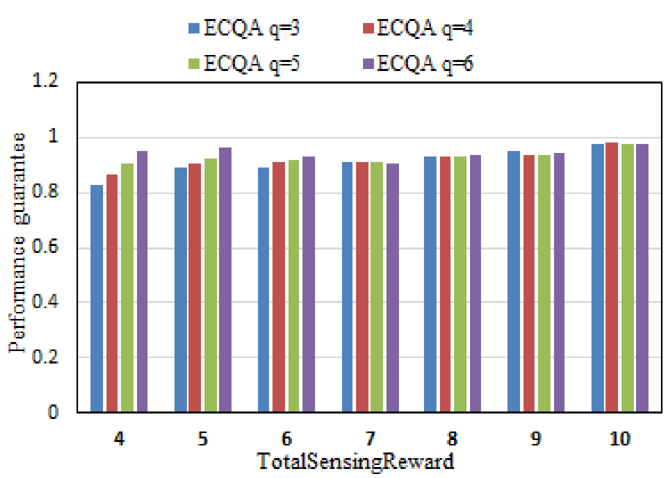

Fig. 8. The initial size of solution is [3, 6], the total sensing reward is [4, 10], the number of period time is 6.

extract 10 vehicles from dataset. From Figs.3 to Figs.8 , we can observe the truth that the algorithm which is proposed in this paper outperforms the one with SAA, and gets closer to the optimal EA. In Fig.3, the STC of our algorithm is larger than the SAA, and if the total sensing reward is enough, the ECQA and EA tends to equal to optimal. The result fit in with reality. In Figs.4 (b), a very brighten evidence is revealed. The performance guarantee of ECQA fluctuates around 0.9 and still provide a performance guarantee larger than $EA \cdot (1-e^{-1})$ as we have proven. This result indicates that in real cases, our algorithm is more likely to achieve full-coverage and ensure the integrity of sensing data. Figs.4 (c) shows, along with the increase of the number of period time m, the STC of both ECQA and competitors become larger and larger. This is because the route of vehicle is scheduled cyclically movement, the larger number of period time, one segment may be covered many time as Fig.2 depicted. Additionally, the performance gap between ECQA and EA stayed nearly constant as m and the performance guarantee is greater than 0.9 consistently as Fig.4 (d) shown. In Figs.4 (e) to (f), we study the important parameter q influence on performance of ECQA, the q is varied from 4 to 10. It is easy to see that, when total sensing reward is less than 7, the STC increase with q, otherwise is even nearly. This result can be understood since the total sensing reward is insufficient, the q is larger, ECQA primarily searches a larger domain for optimal solution, but it takes longer execution time actually. In contract, q has slightly impact on STC, which suggests that we can produce a good performance even with a small q and spend less execution time simultaneously.

V. CONCLUTION

In this paper, we introduce mobile crowd-sensing into vehicular network to produce a vehicle-based crowd sensing network. Due to the quality of crowd-sensing is extraordinarily sensitive to the location of participants, so we take full advantage of predictable mobility pattern of public transport buses which traveling route is scheduled. In this scenario, we need to address a crucial problem of the selection of vehicle to participate in urban sensing for maximizing spatiotemporal coverage. We have proven that the problem of selecting vehicles under a given constraint sensing reward for maximizing spatiotemporal coverage is NP-hard. Then we present the ECQA which aims to select an optimal vehicles collection for maximizing the spatiotemporal coverage by taking the current and future positions into account of each vehicle. Moreover, though the theoretical analysis and a series of simulation on real T-Drive trajectory dataset, we prove that the ECQA can achieve a performance guarantee is still greater than $(1-e^{-1})$ of optimum and obtain better performance than alternative algorithm.

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REFERENCES

[1] Zhu.Y, Bao.Y, Li.B. "On Maximizing Delay-Constrained Coverage of Urban Vehicular Networks[J]." *IEEE Journal on Selected Areas in Communications*, 2012, 30(4):804-817.

[2] Dejun Yang, Guoliang Xue, Xi Fang, and Jian Tang, "Crowdsourcing to smart phones: incentive mechanism design for mobile phone sensing", in*ACM MOBICOM*, 201.

[3] Mohammad Nozari Zarmehri and Ana Aguiar, "Supporting sensing application in vehicular networks", in *ACM CHANTS*, 2012

[4] E.Koukoumidis,L.S.Peh, M.R.Martonosi,"Signalguru:Leveraging mobile phones for collaborative trafc signal schedule advisory", in *Proc. 9th Int. Conf. Mobile Syst., Appl. Serv., ACM*, 2011, pp. 127140.

[5] A. Thiagarajan et al., "Vtrack: Accurate, energy-aware road trafc delay estimation using mobile phones",*7th ACM Conf.Embedded Netw. Sensor Syst., ACM*, 2009, pp. 8598.

[6] P. Dutta, P. M. Aoki, and et al., "Common Sense: participatory urban sensing using a network of handheld air quality monitors," in *SenSys 2009*, pp. 349350.

[7] A.Farshad, M. K. Marina, and F. Garcia, "Urban WiFi characterization via mobile crowdsensing," in *Proc. Netw. Oper. Manage. Symp., IEEE*, 2014, pp. 19.

[8] Feng Z, Zhu Y, Zhang Q, et al. "TRAC: Truthful auction for location-aware collaborative sensing in mobile crowdsourcing[C]" // *INFOCOM, 2014 Proceedings IEEE.* IEEE, 2014:1231-1239.

[9] D. Yang, G. Xue, and et al., "Crowdsourcing to smartphones: Incentive mechanism design for mobile phone sensing," in *MobiCom 2012*, pp. 173184.

[10] S. Reddy, D. Estrin, M. Hansen, and M. Srivastava, "Examining micro-payments for participatory sensing data collections," in *UbiComp 2010*, pp. 3336.

[11] He Z, Cao J, Liu X. "High quality participant recruitment in vehicle-based crowdsourcing using predictable mobility," *Computer Communications. IEEE*, 2015:2542-2550.

[12] L. Kazemi and C. Shahabi, "Geocrowd: Enabling query answering with spatial crowdsourcing," in *ACM SIGSPATIAL 2012*, pp. 189198.

[13] J. Huang and H.-S. Tan, "Vehicle future trajectory prediction with a DGPS/INS-based positioning system," in *American Control Conference*, 2006.

[14] Kang L, Poslad S, Wang W, et al. "A Public Transport Bus as a Flexible Mobile Smart Environment Sensing Platform for IoT" *International Conference on Intelligent Environments. IEEE, 2016*.

[15] Rai A, Chintalapudi K K, Padmanabhan V N, et al. "Zee:zero-effort crowdsourcing for indoor localization[C]"// 2012:293-304.

[16] *https://baike.baidu.com/item*.

[17] MAXIM S. "A note on maximizing a sub-modular set function subject to knapsack constraint [J]" . *Operations Research Letters, 2004*,32(5): 41-43.

[18] Khuller S, Moss A, Naor J. "The budgeted maximum coverage problem [M]".*Elsevier North-Holland*.

[19] Jing Yuan, Yu Zheng, Xing Xie, and Guangzhong Sun. "Driving with knowledge from the physical world." *In The 17th ACM SIGKDD international conference on Knowledge Discovery and Data mining, KDD11,* New York, NY, USA, 2011. ACM.

[20] Jing Yuan, Yu Zheng, Chengyang Zhang, Wenlei Xie, Xing Xie, Guangzhong Sun, and Yan Huang. "T-drive: driving directions based on taxi trajectories". *In Proceedings of the 18th SIGSPATIAL International Conference on Advances in Geographic Information Systems,* GIS 10, pages 99-108, New York, NY, USA,2010. ACM.