Mobile Crowdsensing Game in Vehicular Networks

(Invited)
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***Abstract*—Vehicular crowdsensing takes advantage of the mobility of vehicles to provide location-based services in large-scale areas. In this paper, we analyze vehicular crowdsensing and formulate the interactions between a crowdsensing server and a number of vehicles equipped with sensors in the area of interest as a vehicular crowdsensing game. Each participant vehicle chooses its sensing strategy based on the sensing and transmission costs, and the expected payment by the server, while the server determines its payment policy according to the number and accuracy of the sensing reports. A reinforcement learning based crowdsensing strategy is proposed for vehicular networks, with incomplete system parameters such as the sensing costs of the other vehicles. The server and vehicles achieve their optimal payment and sensing strategies by learning via trials, respectively. Simulation results have verified the efficiency of the proposed mobile crowdsensing systems, showing that the average utilities of the vehicles and the server can be improved and converged to the optimal values in fast speed. Vehicles with less sensing costs are motivated to upload more accurate sensing data.**

***Index Terms*—Vehicular networks, mobile crowdsensing, game theory, Q-learning**

I. INTRODUCTION

With the development of vehicles equipped with sensors, such as camera, microphone, GPS and digital compass, mobile crowdsensing over vehicular networks has become popular. Mobile crowdsensing (MCS) systems consisting of servers in clouds and a number of vehicles provide booming location-based services. Participant vehicles use their embedded sensors to gather the information requested by the servers to provide location-based services, such as urban monitoring [1], road and traffic condition monitoring [2] [3], pollution levels measurements and wildlife habitats monitoring [4]. Due to the inherent mobility, vehicular crowdsensing can improve the sensing coverage.

In order to stimulate vehicles to participate in the crowdsensing tasks, the MCS server has to pay each vehicle according to the quality of its sensing report. A vehicle is motivated to send an accurate report only if the expected payment from the MCS server exceeds its loss due to the energy and time cost in the sensing and transmission process.

Game theory has been used to investigate the interactions between the participants and the MCS servers [5]. Auctions and pricing strategies have been proposed in [6] to stimulate mobile users to participate in crowdsensing applications. For instance, a discriminating payment strategy was proposed in [7] to prevent faked sensing attacks in mobile crowdsensing. However, the crowdsensing depends on the specific type of sensing tasks, which has been ignored by most existing works. For example, in an accumulative sensing task, the MCS server obtains a higher utility by receiving more sensing reports from different vehicles if monitoring traffic conditions in a big city, in the absence of sensing payment. On the other hand, in a best-quality sensing task, such as photo-based application, the MCS server does not benefit from receiving more sensing reports with less quality. Moreover, the mobility of vehicles makes it challenging for each vehicle to obtain accurate information regarding the sensing environment and the other vehicles in time.

Therefore, in this paper, we investigate the crowdsensing in vehicular networks, including two types of crowdsensing applications: the accumulative sensing tasks and the best-quality sensing tasks. The interactions between the MCS server and the vehicles are formulated as a vehicular crowdsensing game, in which the vehicles decide their sensing efforts while the MCS server chooses its payment strategy to maximize its expected utility based on the type of the sensing task. The crowdsensing system applies a discriminating payment scheme, in which each vehicle is paid according to the quality of the sensing report. The Nash equilibrium (NE) of the static vehicular crowdsensing game is investigated for both accumulative sensing tasks and best-quality sensing tasks. We also investigate a dynamic vehicular crowdsensing game, in which the MCS server does not have accurate information of the game, such as the sensing costs of the vehicles and the radio channel conditions. Reinforcement learning technique is used for the MCS server to achieve the optimal payment strategy as a trade off between the sensing quality and the cost. Similarly, we propose a sensing strategy for a vehicle to determine its sensing effort with unknown network state based on reinforcement learning.

The rest of the paper is organized as follows. We review related work in Section II. The system model is presented in Section III. We formulate the vehicular crowdsensing game in Section IV, discuss its NE in section V, and propose a learning crowdsensing scheme in Section VI. The simulation results are presented in Section VII, and conclusions are drawn in Section VIII.

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II. Related Work

In [8], vehicular crowdsensing system was proposed to collect and disseminate traffic information to cars in the same area. In [2], a crowdsensing system was presented to monitor road surface conditions by sensor-equipped vehicles. Autonomous smart mobs in vehicular sensor networks were proposed in [1] for proactive urban monitoring. A vehicle-based mobile surveillance system was presented in [9] to motivate vehicles to monitor signal coverage and efficiency.

A mobile crowdsensing system was designed in [4] to support a wide range of large-scale monitoring applications in smartphones. In [10], a mobile cloud offloading game was proposed for smartphones to analyze the malware detection in a security server. A generic solution was developed for mobile context-aware applications in [11]. A multidimensional context-aware social network architecture was illustrated in [12] to improve the utility of each user. An MCS system based on trust was presented in [13] [14] to encourage collaboration of selfish smartphones.

A mobile crowdsensing game for the case with a single smartphone user in the area of interest was investigated in [7]. In [6], an incentive mechanism was proposed for MCS applications and the Stackelberg equilibrium of the MCS game was derived under the assumption that the utility of each participator is known by the platform. A Bayesian MCS game was investigated with unknown participation efforts of users in [15].

III. System Model

A. Network Model

We consider a vehicular network consisting of M vehicles equipped with sensors, such as cameras and GPSs. An MCS server located in a cloud aims at collecting a certain location-based information as shown in Fig. 1. The vehicles can use their sensors to gather the local information requested by the MCS server in its broadcast message, which also states the range of the payment for the sensing reports, denoted by $\mathbf{B} = \{b_j\}_{0\leq j\leq P}$, where $b_m < b_n$, $\forall 0 \leq m < n \leq P$, and b_P is the highest payment to the vehicle.

Once receiving the MCS message broadcasted by the server, vehicle i determines whether to participate in the MCS service and the efforts to perform the sensing task, in the form of data accuracy and denoted by x_i. For simplicity, the sensing effort is quantized into $L+1$ levels, i.e., $x_i \in \mathbf{A} = \{0, 1, 2, ..., L\}$. A vehicle does not participate in the MCS service if $x_i = 0$, while it applies its full sensing effort if $x_i = L$.

As shown in Fig. 1, the server pays each vehicle according to the classification results of the received sensing reports. More specifically, the payment strategy is denoted by $\mathbf{y} = [y_j]_{0\leq j\leq L}$, where $y_j \in \mathbf{B}$ is the payment offered to the vehicle choosing action $j \in \mathbf{A}$.

B. Channel Model

In vehicular networks, the channel state from a vehicle to the MCS server changes over time due to vehicle mobility. The moving speed of a vehicle affects the channel coherence time

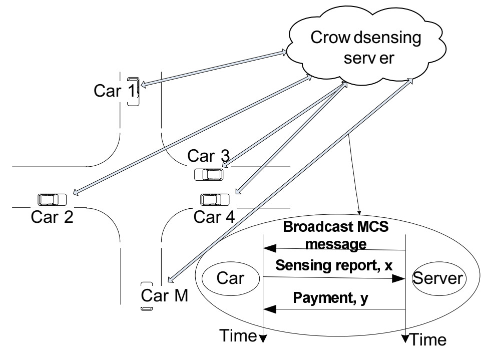


Fig. 1. Illustration of a vehicular crowdsensing system consisting of a mobile crowdsensing server and M vehicles.

because of the Doppler shift, further leads to variant channel fading [16]. For simplicity, each vehicle is assumed to send sensing report with constant transmit power, and the signal-to-noise ratio (SNR) of the signals sent by the vehicles are quantized into $N+1$ levels, denoted by $\varrho = \{H_j\}_{0\leq j\leq N}$, where $H_m < H_n$, $\forall 0 \leq m < n \leq N$.

The channel state of each vehicle is modeled with a Markov chain with $N+1$ states, given by $\{H_j\}_{0\leq j\leq N}$, where the transmit probability for the channel state h to change from H_m to H_n during a time slot is denoted by $P_{m,n}$, i.e.,

$$P_{m,n} = \Pr(h = H_n | h = H_m), \forall 0 \leq m, n \leq N. \qquad (1)$$

IV. Vehicular Crowdsensing Game

The interactions among an MCS server and M vehicles are formulated as a vehicular crowdsensing game. Each vehicle is assumed to be rational, selfish and autonomous to decide its sensing accuracy. The actions of the M vehicles, denoted by $\mathbf{x} = [x_i]_{1\leq i\leq M}$, correspond to the accuracy of the sensing reports, with $0 \leq x_i \leq L$. The sensing cost of the vehicle i is denoted by $\mathbf{C}_i = [c_{i,j}]_{0\leq j\leq L}$, where $c_{i,j}$ is the unit cost to the vehicle i, if taking sensing action $x_i = j$.

The channel state between vehicle and the MCS server affects the transmission cost of the vehicle and can be indicated by the SNR, denoted by h. The immediate utility of the vehicle i is based on the payment and the sensing cost, given by

$$u_i(x_i, \mathbf{y}) = y_{x_i} - \frac{x_i c_{i,x_i}}{\log(1+h)}. \qquad (2)$$

The MCS server benefits from the sensing reports of the vehicles, and evaluates the sensing reports based on the type of the MCS application.

1) Accumulative sensing tasks: For the MCS applications that benefit from receiving more number of sensing reports, an MCS sever has to pay all the vehicles that participate in its MCS service. For example, the MCS server for a pollution monitoring application can in general derive a more accurate measurement by receiving more samples measured by different vehicles in the area. In this case, the gain of the

MCS server depends on all the received sensing reports, and the contribution of the reports, denoted by G, is given by

$$G(\mathbf{x}) = \sum_{i=1}^{M} \beta x_i, \tag{3}$$

where β is the unit benefit that the MCS server obtains from the sensing reports. Each vehicle is paid according to the accuracy of the sensing data. The immediate utility of the MCS server is given by

$$u_s(\mathbf{x}, \mathbf{y}) = G(\mathbf{x}) - \sum_{i=1}^{M} y_{x_i}. \tag{4}$$

2) Best-quality sensing tasks: For the MCS applications that depend on the sensing report of the highest quality, the MCS server only pays the vehicle that sends the best sensing report. For instance, the server requesting a photo-based MCS application does not gain from the sensing photos with lower resolutions in the same location and thus has no motivation to pay the corresponding vehicles. The contribution of the sensing reports is given by

$$G'(\mathbf{x}) = \max_{1 \le i \le M} \beta x_i. \tag{5}$$

The vehicle uploading the best-quality sensing report is paid, while the others do not receive any payment. The immediate utility of the MCS server based on the gain from the received sensing data and the payment paid to the vehicle whose sensing data is selected, can be written as

$$u_s'(\mathbf{x}, \mathbf{y}) = G'(\mathbf{x}) - y_{\max_{1 \le i \le M} x_i}. \tag{6}$$

In summary, the above vehicular crowdsensing game is denoted by $\mathbf{G} = \langle \{s, 1, 2, ..., M\}, \{\mathbf{y}, \mathbf{x}\}, \{u_s, u_{1 \le i \le M}\} \rangle$, in which the MCS server and the M vehicles take payment policy $\mathbf{y}$ and sensing strategies $\mathbf{x}$ to maximize their individual utilities u_s and u_i, respectively.

V. Nash Equilibrium of Vehicular Crowdsensing Game

The Nash equilibrium (NE) of the vehicular crowdsensing game $\mathbf{G}$ is denoted as $(\mathbf{x}^*, \mathbf{y}^*)$, where $\mathbf{x}^* = [x_i^*]_{0 \le i \le M}$ is the sensing accuracy of M vehicles, $\mathbf{y}^* = [y_j^*]_{0 \le j \le L}$ is the payment policy of the MCS server, x_i is the sensing effort of vehicle i, and y_j is the payment of the MCS server to vehicles with sensing effort j. The strategies in NE are the optimal responses of the players that know all the system parameters in the game. By definition, we have

$$x_i^* = \arg\max_{x_i \in \mathbf{A}} u_i(x_i, \mathbf{y}^*), \quad 1 \le i \le M \tag{7}$$

$$\mathbf{y}^* = \arg\max_{y_j \in \mathbf{B}} u_s(\mathbf{x}^*, \mathbf{y}), \quad 0 \le j \le L. \tag{8}$$

First, in a special situation with $L = 1$, vehicle i sends a good report (i.e., $x_i = 1$) or keeps silence (i.e., $x_i = 0$), and the corresponding sensing cost vector is $\mathbf{C}_i = [0, c_i]$. It's clear that $y_0 = 0$ and thus the optimal payment strategy of the MCS server is given by $\mathbf{y}^* = [0, y^*]$. The payment strategy for the MCS server to stimulate a given vehicle to participate in the accumulative sensing tasks is given by the following.

Proposition 1. *In the static vehicular crowdsensing game* $\mathbf{G}$ *with accumulative sensing tasks and* $L = 1$*, vehicle* i *is motivated to send an accurate sensing report, i.e.,* $x_i^* = 1$*, if*

$$y^* \ge \frac{c_i}{\log(1+h)}. \tag{9}$$

Proof. According to (7), we have $x_i^* = 1$, if and only if $u_i(1, \mathbf{y}^*) \ge u_i(0, \mathbf{y}^*)$. As $u_i(0, \mathbf{y}^*) = 0, \forall 1 \le i \le M$, by (2), we have $u_i(1, \mathbf{y}^*) \ge 0$, yielding

$$u_i(1, \mathbf{y}^*) = y^* - \frac{c_i}{\log(1+h)} \ge 0, \tag{10}$$

and thus we have (9). □

Remark: If the MCS server offers a sufficient payment for accurate sensing reports, i.e., $y^* \ge c_i/\log(1+h)$, vehicle i is motivated to send an accurate sensing report.

Proposition 2. *In the static vehicular crowdsensing game* $\mathbf{G}$ *with accumulative sensing tasks and* $L = 1$*, vehicle* i *has no motivation to perform the sensing task, i.e.,* $x_i^* = 0$*, if*

$$y^* < \frac{c_i}{\log(1+h)}. \tag{11}$$

Proof. Similar to that of Proposition 1. □

Remark: If the payment offered by the MCS server is lower than the vehicle's cost to send a good report, i.e., $y^* < c_i/\log(1+h)$, the vehicle does not send an accurate sensing report.

Theorem 1. *The NE* $(\mathbf{x}^*, y^*)$ *of the static vehicular crowdsensing game* $\mathbf{G}$ *with accumulative sensing tasks,* M *vehicles and* $L = 1$ *is given by*

$$x_i^* = \begin{cases} 1, & i = i^* \\ 0, & o.w. \end{cases} \tag{12}$$

$$y^* = \min_{1 \le i \le M} \frac{c_i}{\log(1+h)}, \tag{13}$$

where

$$i^* = \arg\min_{1 \le i \le M} \frac{c_i}{\log(1+h)}. \tag{14}$$

Proof. According to (8), we have $u_s(\mathbf{x}^*, \mathbf{y}^*) \ge u_s(\mathbf{x}^*, \mathbf{y}), \forall \mathbf{y}$. As $u_s(\mathbf{x}^*, [0, 0]) = 0$, we have $u_s(1, y^*) \ge 0$. As shown in (4), u_s monotonically decreases with y, indicating that y^* is the smallest feasible positive solution of $\sum_{i=1}^{M} x_i^* > 0$. By Proposition 1 and Proposition 2, we have (13). □

Remark: If the MCS server requests for accurate sensing report, Theorem 1 shows that a single vehicle sends a valid report while the others do not respond to avoid data redundancy and transmission confliction.

Corollary 1. *In the static vehicular crowdsensing game* $\mathbf{G}$ *with* $L = 1$*, all the* M *vehicles apply their highest sensing efforts, if*

$$y^* = \max_{1 \le i \le M} \frac{c_i}{\log(1+h)}. \quad (15)$$

Proof. Similar to that of Theorem 1. □

For the case with $L = 2$, each of the M vehicles chooses to send an accurate sensing report (i.e., $x = 2$), a low quality sensing report (i.e., $x = 1$), or keep silence (i.e., $x = 0$), and the corresponding sensing cost for vehicle i is $\mathbf{C}_i = [0, c_{i,1}, c_{i,2}]$. It's obvious that $y_0 = 0$, thus the corresponding optimal payment given by the server is $\mathbf{y}^* = [0, y_1^*, y_2^*]$.

Proposition 3. *In the static vehicular crowdsensing game* $\mathbf{G}$ *with accumulative sensing tasks and* $L = 2$*, vehicle* i *is motivated to send an accurate sensing report, i.e.,* $x_i^* = 2$*, if*

$$\begin{cases} y_1^* & \le y_2^* - \frac{2c_{i,2} - c_{i,1}}{\log(1+h)} \\ y_2^* & \ge \frac{2c_{i,2}}{\log(1+h)} \end{cases}. \quad (16)$$

Proof. According to (7), $x_i^* = 2$, if and only if $u_i(2, \mathbf{y}^*) \ge u_i(1, \mathbf{y}^*)$ and $u_i(2, \mathbf{y}^*) \ge u_i(0, \mathbf{y}^*)$. As $u_i(0, \mathbf{y}^*) = 0$, $\forall 1 \le i \le M$, by (2), $u_i(2, \mathbf{y}^*) \ge 0$ yields

$$y_2^* - \frac{2c_{i,2}}{\log(1+h)} \ge 0. \quad (17)$$

As $u_i(2, \mathbf{y}^*) \ge u_i(1, \mathbf{y}^*)$, we have

$$y_2^* - \frac{2c_{i,2}}{\log(1+h)} \ge y_1^* - \frac{c_{i,1}}{\log(1+h)}. \quad (18)$$

By (17) and (18), we have (16). □

Proposition 4. *In the static vehicular crowdsensing game* $\mathbf{G}$ *with accumulative sensing tasks and* $L = 2$*, vehicle* i *is motivated to send a low quality sensing report, i.e.,* $x_i^* = 1$*, if*

$$\begin{cases} y_1^* & \ge \frac{c_{i,1}}{\log(1+h)} \\ y_2^* & \le y_1 - \frac{c_{i,1} - 2c_{i,2}}{\log(1+h)} \end{cases}. \quad (19)$$

Proof. Similar to that of Proposition 3. □

Proposition 5. *In the static vehicular crowdsensing game* $\mathbf{G}$ *with accumulative sensing tasks and* $L = 2$*, vehicle* i *has no motivation to participate in the crowdsensing, i.e.,* $x_i^* = 0$*, if*

$$\begin{cases} y_1^* < \frac{c_{i,1}}{\log(1+h)} \\ y_2^* < \frac{2c_{i,2}}{\log(1+h)} \end{cases}. \quad (20)$$

Proof. Similar to that of Proposition 3. □

Remark: Quality of the sensing report closely depends on the payment offered by the server. The vehicle is motivated to upload an accurate report if the payment y_2^* is higher than y_1^*, otherwise, the vehicle tends to upload a rough report. If the sensing cost is high compared with the payment offered by the server, the vehicle is motivated not to response.

Theorem 2. *The NE* $(x^*, \mathbf{y}^*)$ *of a static vehicular crowdsensing game* $\mathbf{G}$ *with* $M = 1$ *and* $L = 2$ *is given by*

$$\begin{cases} x^* = 2 \\ \mathbf{y}^* = [0, 0, \frac{2c_2}{\log(1+h)}] \end{cases}. \quad (21)$$

Proof. According to (8), we see that $u_s(x^*, \mathbf{y}^*) \ge u_s(x^*, \mathbf{y}), \forall \mathbf{y}$. As $u_s(x^*, [0, 0, 0]) = 0$, we have $u_s(2, \mathbf{y}^*) \ge 0$. As shown in (4), u_s is monotonically decreasing in $\mathbf{y}$, and we have (21) by Proposition 3. □

VI. Vehicular Crowdsensing with Q-learning

If system parameters such as the sensing costs of the vehicles and the channel conditions are available to all players in the vehicular crowdsensing game, the vehicles can use their optimal sensing policies as shown in the NE. However, it is impractical to accurately estimate all the system parameters in time. Thus Q-learning technique can be used to reach the optimal strategies via trials.

The MCS server first determines its payment policy, which affects the vehicles' sensing efforts in the future. The ϵ-greedy policy is employed by the vehicles to choose their sensing accuracy, in which the sensing action with the highest expected utility u_i is chosen with a high probability $1 - \epsilon$, $0 < \epsilon \le 1$, while the other actions are selected with an equal probability if otherwise. Thus the sensing accuracy of the vehicle i is given by

$$\Pr(x_i = x) = \begin{cases} 1 - \epsilon, & x = x^* \\ \frac{\epsilon}{L}, & x \in \mathbf{A}, x \ne x^* \end{cases}, \quad (22)$$

where

$$x^* = \arg\max_{x \in \mathbf{A}} u_i(x, \mathbf{y}). \quad (23)$$

The MCS server determines its payment policy based on the Q-learning technique. More sepecifically, for the accumulative sensing tasks, the MCS server calculate the number of the received sensing reports with quality level j, denoted by N_j, i.e.,

$$N_j = \sum_{i=1}^{M} I(x_i = j), \quad (24)$$

where $I(\cdot)$ is the indicator function. The system state for the server in this case at iteration k is denoted by $\mathbf{s}^k = [N_j]_{0 \le j \le L} \in \mathbf{S}$. Thus the immediate utility of the server in (4) becomes

$$u_s(\mathbf{s}, \mathbf{y}) = \sum_{j=0}^{L} \beta j N_j - \sum_{j=0}^{L} y_j N_j. \quad (25)$$

For the best-quality sensing tasks, the system state for the server at iteration k is denoted by $s'^k = \max_{1 \le i \le M} x_i \in \mathbf{S}'$. The immediate utility of the server in (6) becomes

$$u_s'(s', \mathbf{y}) = \beta s' - y_{s'}. \quad (26)$$

Let $Q(\mathbf{s}, \mathbf{y})$ denote the Q function of the state $\mathbf{s}$ and the payment policy $\mathbf{y}$ and $V(\mathbf{s})$ denote the value function of the

Algorithm 1 Payment strategy of the MCS server.

Set $\alpha = 0.8$, $\delta = 0.7$.
Initialize $Q(\mathbf{s}, \mathbf{y}) = \mathbf{0}$, $V(\mathbf{s}) = \mathbf{0}$, $\forall \mathbf{s}, \mathbf{y}$, $k = 1$.
Repeat (for each episode)
  Observe the initial system state $\mathbf{s}^1$;
  For k=1, 2, 3,...
    Choose the payment $\mathbf{y}^k \in \mathbf{B}$ via (29);
    Observe the subsequent state s^{k+1} and immediate reward u_s;
    Update $Q(\mathbf{s}^k, \mathbf{y}^k)$ via (27);
    Update $V(\mathbf{s}^k)$ via (28);
  End for
End repeat

state $\mathbf{s}$ indicating the highest value of the state. At the k-th iteration, the server observes the current system state $\mathbf{s}^k$ and determines its payment strategy $\mathbf{y}^k$ accordingly. The updating process for the server is given by

$$Q(\mathbf{s}^k, \mathbf{y}^k) \leftarrow (1-\alpha)Q(\mathbf{s}^k, \mathbf{y}^k) + \alpha(u_s(\mathbf{s}^k, \mathbf{y}^k) + \delta V(\mathbf{s}^{k+1})) \tag{27}$$

$$V(\mathbf{s}^k) = \max_{y_j \in \mathbf{B}} Q(\mathbf{s}^k, \mathbf{y}), \quad 0 \le j \le L, \tag{28}$$

where $\alpha \in (0, 1]$ is the learning rate and $\delta \in [0, 1]$ is the discounting factor indicating the weight of a future payoff over the current payoff. An ϵ'-greedy policy is used for the server to choose its payment policy, which is given by

$$\Pr(\mathbf{y}^k = \mathbf{y}) = \begin{cases} 1-\epsilon', & \mathbf{y} = \mathbf{y}^* \\ \frac{\epsilon'}{|\mathbf{B}|-1}, & \text{o.w.} \end{cases}, \tag{29}$$

where $|\mathbf{B}|$ denotes the size of the payment set, and

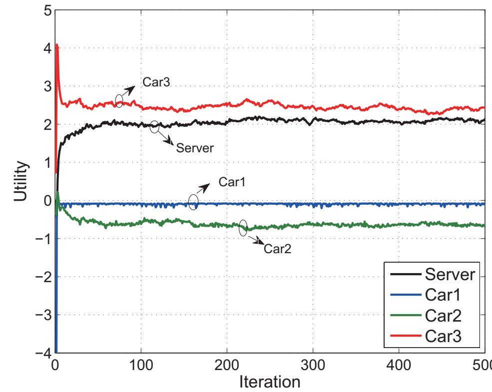
$$\mathbf{y}^* = \arg\max_{y_j \in \mathbf{B}} Q(\mathbf{s}^k, \mathbf{y}), \quad 0 \le j \le L. \tag{30}$$

The payment process for the accumulative sensing tasks is similar to these and is summarized in Algorithm 1.

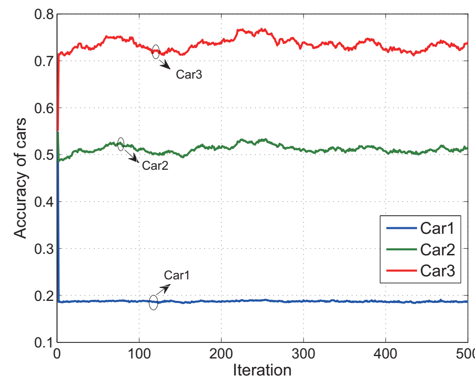
VII. Simulation Results

Simulations have been performed to evaluate the performance of the vehicular crowdsensing game $\mathbf{G}$ with the sensing efforts set $\{0, 0.1, 0.2, ..., 1\}$, the unit sensing cost vector is $\omega = [0, 0.1, 0.3, 0.6, 1, 1.5, 2.1, 2.8, 3.6, 4.5, 5.5]$, $b_p = 15$, $\varrho = \{0, 0.3, 0.8, 1, 1.5, 2\}$ with initial probability distribution $P = [0.1, 0.2, 0.2, 0.3, 0.1, 0.1]$, and $\beta = 10$, if not specified otherwise. It assumes that the normalized SNR transfers from a given state to its two adjacent states with probability 0.1. The simulations focused on the best-quality sensing tasks, where the server always chooses the report with the highest accuracy.

The performance of the vehicular crowdsensing game for a server with Q-learning payment strategy and 3 cars with ϵ-greedy sensing strategies is presented in Fig. 2. The unit sensing costs of the car 1, 2 and 3 in this situation are given as $C_1 = 5\omega$, $C_2 = \omega$ and $C_3 = 0.5\omega$, respectively. As shown in Fig. 2 (a), the utility of the server sharply increases not long after the start of learning, and eventually converges to the maximum value, i.e., $u_s^* = 2$. In addition, it is noted that the car with the lowest unit sensing cost to the same task like car 3 in Fig. 2 (a) benefits most from this sensing process. It can be observed from Fig. 2 (b) that the less sensing cost motivates the vehicle to send a more accurate sensing report, which is more probable to be admitted by the server and rewarded.



(a) Utility

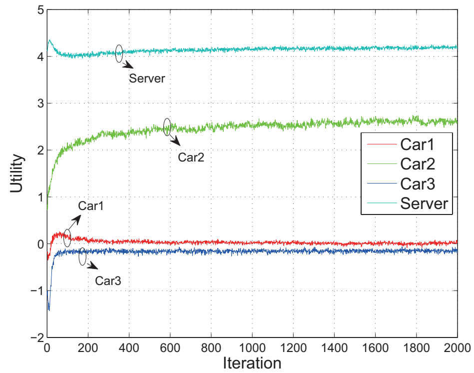


(b) Action

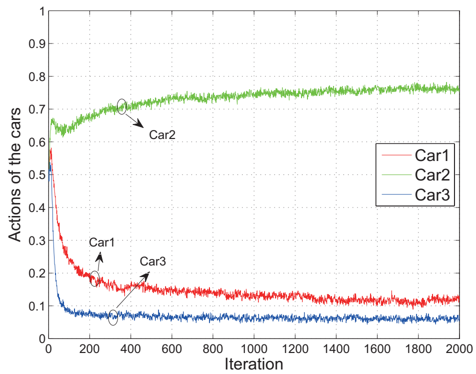
Fig. 2. Performance of the vehicular crowdsensing system with learning-based payment strategy, in which $C_1 = 5\omega$, $C_2 = \omega$ and $C_3 = 0.5\omega$, respectively.

The performance of the MCS server and 3 cars with $C_1 = 0.5\omega$, $C_2 = 0.1\omega$ and $C_3 = 0.9\omega$ is presented in Fig. 3. The server applies a static payment policy to maximize the immediate utility, while the three cars use Q-learning to update their sensing strategies. With the capability of learning, sensing cars can achieve stable profits, which can be seen in Fig. 3 (a). Similarly, the car with the lowest sensing cost (i.e., Car 2 with 0.1ω) among vehicles obtains the highest utility, i.e., $u_2^* = 2.6$ after 2000 iterations. In addition, Fig. 3 (a) also shows slightly decline in utility of the sever during the iterations. The reason is that the lower sensing cost motivates the car to report more accurate data for higher reward, while the others with larger sensing costs are not willing to upload data to the server as shown in Fig. 3 (b).

The performance of the vehicular crowdsensing game for a server with Q-learning payment strategy and a number of vehicles with ϵ-greedy sensing strategies is presented in Fig. 4, in which $C_i = d\omega$, $d \in \{20, 10, 5, 2, 1, 0.8, 0.6, 0.4, 0.2, 0.1\}$ and $P_d = \{0.01, 0.02, 0.05, 0.08, 0.1, 0.12, 0.2, 0.2, 0.12, 0.1\}$. As shown in Fig. 4, the utility of the server increases with the



(a) Utility



(b) Action

Fig. 3. Performance of the vehicular crowdsensing system with learning-based sensing strategy, in which $C_1 = 0.5\omega$, $C_2 = 0.1\omega$ and $C_3 = 0.9\omega$, respectively.

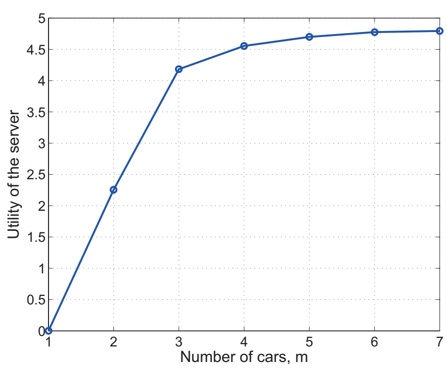


Fig. 4. Average utility of the MCS server in a vehicular network with M cars, in which $C = d\omega$.

number of the sensing cars, because the server is more likely to receive a good sensing report with more vehicle participants joining in sensing.

VIII. Conclusions

We have formulated the interactions between a crowdsensing server and a number of vehicles as a vehicular crowdsensing game, in which each vehicle chooses its sensing effort based on the cost and the expected payment by the server, while the server makes payment based on the number and accuracy of the received sensing reports. We have presented the NE of the vehicular crowdsensing game. For the dynamic environment with unknown system parameters, such as sensing costs of the vehicles, we have proposed a learning-based sensing strategies and payment policy for the vehicles and the server, respectively. Simulation results have shown that the proposed MCS system with Q-learning can significantly improve the utilities of both MCS servers and vehicles. Vehicles with less sensing costs are motivated to upload more accurate sensing reports to achieve larger utilities.

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