

Vehicle Tracking in Wireless Sensor Networks via Deep Reinforcement Learning

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Abstract—Vehicle tracking has become one of the key applications of wireless sensor networks in the fields of rescue, surveillance, traffic monitoring, etc. However, the increased tracking accuracy requires more energy consumption. In this letter, a decentralized vehicle tracking strategy is conceived for improving both tracking accuracy and energy saving, which is based on adjusting the intersection area between the fixed sensing area and the dynamic activation area. Then, two deep reinforcement learning (DRL) aided solutions are proposed, relying on the dynamic selection of the activation area radius. Finally, simulation results show the superiority of our DRL-aided design.

Index Terms—Sensor networks, deep reinforcement learning (DRL), vehicle tracking, wireless sensor networks (WSNs).

I. INTRODUCTION

With the advances in the fabrication technologies that integrate the sensing and the wireless communication, a large-scale wireless sensor networks (WSNs) are formed in the desired fields by deploying dense tiny sensor nodes. Vehicle tracking in WSNs has several prominent merits: First, the sensing unit is close to the vehicle; thus, the sensed data will be of a qualitatively good geometric fidelity via vehicle-to-infrastructure (V2I) technology [1]; second, the information about the target is simultaneously generated by multiple sensors and thus contains redundancy [2]. However, there still exist some unsolved problems as far as vehicle tracking in WSNs is concerned. The first issue is how to guarantee the vehicle to be tracked by sensor nodes. Second is how to maximize the tracking accuracy with the limited resources of WSNs, such as the energy restriction of each node [3].

There are two strategies based on the data processing mechanism, namely centralized strategy and decentralized strategy. Specifically, in centralized strategy, a sensor is artificially selected as a cluster head, and the tracking estimation is performed at this node with all received data [4]. However, the tasks at the cluster head may be overloaded in this strategy. In each iteration of the decentralized strategy, each cluster uses the data from their neighbors to refine its local estimate [5]. Therefore, although the head is closer to the data source than the fixed head in centralized strategy, it has higher energy efficiency. Meanwhile, the works in [6] point out that deep reinforcement learning (DRL) is a problem-solving tool and suitable for decentralized systems in WSNs.

The existing decentralized tracking strategies in WSNs are based on the prediction position to activate a fixed number of nodes, which will result in unnecessary energy consumption. Thus, we propose a dynamic activation area adjustment scheme based on DRL to save energy consumption while ensuring tracking accuracy. Based on this, we first formulate the problem as a Markov decision process (MDP). Then, we construct the optimization problem as maximizing average rewards of MDP, where the reward consists of both tracking accuracy

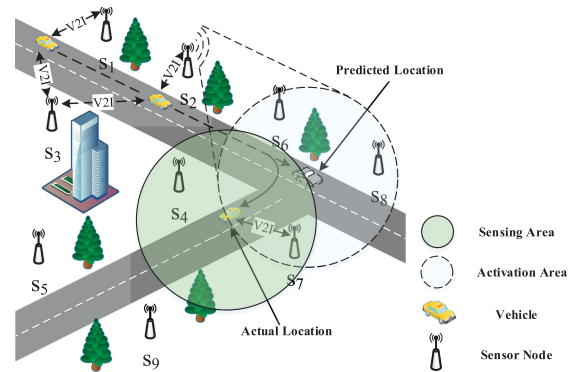


Fig. 1. Illustration of vehicle tracking in WSNs.

and energy consumption. Furthermore, we propose a pair of schemes based on a deep Q network (DQN) and on deep determined policy gradient (DDPG) to maximize average rewards of the MDP. In simulation, our proposed DQN- and DDPG-based algorithms outperform the conventional Q-learning-based method in terms of tracking accuracy and energy consumption.

II. SYSTEM MODEL

Fig. 1 illustrates an vehicle tracking scenario in WSNs, which consists of a single vehicle and multiple sensor nodes. The WSNs start tracking and broadcasting when the object vehicle appears in its monitoring area. Consider that the time slots are denoted by $t = 1, 2, \dots, T$, with unequally duration $\tau(t)$ seconds. The vehicle drives into the monitoring area of the WSNs at time slot $t = 1$, and leaves the WSNs or the WSNs loss vehicle at $t = T$. Let the vehicle's vector is denoted by $\mathbf{x}(t) = [x_t, v_t^x, y_t, v_t^y]^T$, where $\mathbf{I}(t) = [x_t, y_t]^T$ is the 2-D position of the vehicle, and $[v_t^x, v_t^y]^T$ is the velocity of the vehicle at time slot t on the plane. As shown in Fig. 1, the connection between the sensor nodes and the vehicle can be established by V2I within a certain range, and thus, the radius r_s of sensing area $n_s(t)$ is fixed. Moreover, the WSNs activate the sensors in

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activation area $n_a(t)$ with radius $r_a(t)$ in advance, for tracking with dynamic energy consumption. Additionally, let the sensors in set of intersection area $S_{\text{int}}(t) = n_s(t) \cap n_a(t)$ denote as $i = 1, 2, \dots, |m(t)|$, where $m(t)$ is the collection of sensors in $S_{\text{int}}(t)$, and $|m(t)| = \text{card}[m(t)]$ represents the amount of elements in set $m(t)$.

At time slot $t - 1$, WSNs enable an activation area $n_a(t)$ in advance, which is an area based on the predicted vector $\hat{\mathbf{x}}'(t)$ and $r_a(t)$. When the vehicle moves from $t - 1$ to t , sensors in $m(t)$ track the vehicle cooperatively, and then only one sensor node is selected for transmitting data to the sensors in $n_a(t + 1)$.

A. Motion Model

In our model, the vehicle's vector is 4-D. For simplicity, we model the vehicle's motion vector as a linear moving model [7] as $\mathbf{x}(t + 1) = \mathbf{A}\mathbf{x}(t) + \mathbf{D}\mathbf{w}(t)$, where \mathbf{A} represents the vector transition matrix, \mathbf{D} is the transition duration matrix, and $\mathbf{w}(t)$ denotes the noise adding on the vehicle, which is a zero-mean white Gaussian noise with covariance matrix \mathbf{Q} .

B. Measurement Model

The vehicle's measurement model can be given by $\mathbf{z}_i(t) = \mathbf{H}\mathbf{x}(t) + \mathbf{v}_i(t)$, where $\mathbf{z}_i(t)$ represents the measurement of the i th sensor at time t , and the measurement matrix \mathbf{H} is assumed to be same for each sensor node. $\mathbf{v}_i(t)$ is the measurement noise of the i th sensor, which is assumed to be a zero-mean white Gaussian with covariance matrix \mathbf{R}_i . Additionally, the observation noises that are added on different sensor nodes are independent.

C. Filtering Model

In this letter, we employ the Kalman filtering approach for WSNs to track the vehicle. To be specific, the iterative process with motion and measurement model can be given by [5] as

$$\hat{\mathbf{x}}'(t) = \mathbf{A}\hat{\mathbf{x}}(t - 1) + \mathbf{D}\mathbf{w}(t - 1) \quad (1a)$$

$$\mathbf{P}'_i(t) = \mathbf{A}\mathbf{P}_i(t - 1)\mathbf{A}^T + \mathbf{Q}(t - 1) \quad (1b)$$

where the priori estimated vector $\hat{\mathbf{x}}(t - 1)$ and its covariance $\mathbf{P}_i(t - 1)$ is obtained from the data in time slot $t - 1$. Then, the priori data is modified by $\hat{\mathbf{x}}'(t)$ and $\mathbf{z}(t)$

$$\mathbf{P}_i(t) = [\mathbf{P}'_i(t)^{-1} + \mathbf{H}^T[\mathbf{R}_i(t)]^{-1}\mathbf{H}]^{-1} \quad (2a)$$

$$\hat{\mathbf{x}}(t) = \mathbf{P}_o(t) [\mathbf{P}'_o(t)^{-1}\hat{\mathbf{x}}'(t) + \mathbf{H}^T[\mathbf{R}_o(t)]^{-1}\mathbf{z}_o(t)]. \quad (2b)$$

Herein, $\mathbf{z}_o(t) = \mathbf{H}\hat{\mathbf{x}}(t) + \min_i \mathbf{v}_i(t)$ denotes the optimal measurement by broadcasting the data of selected sensor nodes in $m(t)$, where $\mathbf{R}_o(t) = \mathbb{E}[\min_i \mathbf{v}_i(t)]$. The goal of this selection strategy can help improve tracking accuracy, namely the smaller $\mathbf{P}_i(t)$ is, the better the estimation quality becomes [8]. Next, we select a sensor with best measuring performance according to $\mathbf{P}_o(t) = \min_i \text{tr}(\mathbf{P}_i(t))$, where $\mathbf{P}_o(t)$ is the data that the fusion center needs to transmit to $n_a(t + 1)$.

D. Time Model

In this letter, for obtaining the time interval of tracking vehicle in WSNs, we quantify the time based on the formula as [9]

$$\tau[c(\mathbf{p}_1, \mathbf{p}_2)] = \frac{N_b}{B \log_2 \left(1 + \frac{P_t c(\mathbf{p}_1, \mathbf{p}_2)}{\sigma^2} \right)} \quad (3a)$$

$$c(\mathbf{p}_1, \mathbf{p}_2) = \left[\frac{\rho_0}{\|\mathbf{p}_1 - \mathbf{p}_2\|_2} \right] \quad (3b)$$

where ρ_0 in (3b) denotes the path loss per meter; thus, $c(\mathbf{p}_1, \mathbf{p}_2)$ is the channel gain between positions \mathbf{p}_1 and \mathbf{p}_2 . In (3a), N_b denotes the bits of each task, B is the communication bandwidth, P_t is transmission power, and σ^2 is the power of Gaussian white noise in WSNs. Therefore, the data transmission duration is calculated as $\tau[c(\mathbf{p}_1, \mathbf{p}_2)]$. Furthermore, the processing time consists of following three parts.

- 1) *Data Gathering Time Model*: Based on the estimated vector $\hat{\mathbf{x}}(t - 1)$, activation radius $r_a(t)$, and the sensing area $n_s(t)$, the sensors in $m(t)$ will detect the vehicle. Let $\mathbf{p}_1 = \hat{\mathbf{l}}(t)$ and $\mathbf{p}_2 = \mathbf{p}(i)$, $i = 1, 2, \dots, |m(t)|$; thus, $\tau'_1(t) = \tau[c(\hat{\mathbf{l}}(t), \mathbf{p}(i))]$, where the estimated position is $\hat{\mathbf{l}}(t) = \mathbf{H}\hat{\mathbf{x}}(t)$. In addition, let $\tau'_1(t) = \max_i \tau[c(\hat{\mathbf{l}}(t), \mathbf{p}(i))]$ be the longest duration, based on the channel gain with the distance between the vehicle and the furthest node i .
- 2) *Data Fusion Time Model*: After data gathering, the sensors in $m(t)$ should establish a communication mechanism to find the optimal tracking data. Thus, the system randomly selects a node J as a virtual data fusion center, which is responsible for receiving data from other sensor node $j = 1, 2, \dots, |m(t)|$, $j \neq J$. Let $\mathbf{p}_1 = \mathbf{p}(J)$ and $\mathbf{p}_2 = \mathbf{p}(j)$; thus, $\tau'_2(t) = \tau[c(\mathbf{p}(J), \mathbf{p}(j))]$. Let $\tau'_2(t) = \max_j \tau[c(\mathbf{p}(J), \mathbf{p}(j))]$ represent the duration of total data fusion process, based on the channel gain with distance between J and the furthest node j .
- 3) *Data Broadcast Time Model*: After data fusion in $m(t)$, the center J transfers the optimal data to the sensors in $n_a(t + 1)$. Let $\mathbf{p}_1 = \mathbf{p}(J)$ and $\mathbf{p}_2 = \mathbf{p}(k)$, $k = 1, 2, \dots, |m_a(t + 1)|$; thus, $\tau'_3(t) = \tau[c(\mathbf{p}(J), \mathbf{p}(k))]$. Similarly, $|m_a(t + 1)|$ denotes the amount of sensors of $n_a(t + 1)$, and $\tau'_3(t) = \max_k \tau[c(\mathbf{p}(J), \mathbf{p}(k))]$ denotes the total data broadcast duration based on the minimum channel gain with the longest distance between J and the sensor k .

In summary, the time duration in each round includes these three parts $\tau(t) = \tau'_1(t) + \tau'_2(t) + \tau'_3(t)$.

III. PROBLEM FORMULATION

This letter solves the problem of improving tracking accuracy and energy saving when tracking a vehicle in WSNs. Explicitly, the number of the sensor nodes for tracking contributes to the tracking accuracy [5]. Nevertheless, with the increase of the sensor nodes, the energy consumption for communication and data processing becomes higher. To efficiently track the vehicle, we propose a dynamic activation area adjustment scheme to balance the tradeoff between tracking accuracy and energy consumption. In this section, we model this scheme as an MDP based on the nature of the dynamic decision-making problem given in the following.

- 1) *State Space*: Let $\mathcal{S} = \{s(t) | t = 1, 2, \dots, T\}$ denote the state space of the WSNs, where $s(t) = \{\hat{\mathbf{x}}'(t), \hat{\mathbf{x}}(t), r_a(t)\}$ includes the estimated vector $\hat{\mathbf{x}}'(t)$ of the vehicle in time slot t , the estimated vector of vehicle $\hat{\mathbf{x}}(t)$ based on $\hat{\mathbf{x}}'(t)$ and the measurement $\mathbf{z}_i(t)$, and the radius of the activation area $r_a(t)$. The elements in \mathcal{S} except $r_a(t)$ are described in the Kalman filtering model.
- 2) *Action Space*: Let \mathcal{A} denote the action space of the WSNs, where $r_a(t) \in \mathcal{A}$ is the radius of $n_a(t)$.
- 3) *Reward*: Assume that $n_a(t)$ and $n_s(t)$ are circles with radii $r_a(t)$ and r_s , respectively, and the prediction error in time slot t is denoted as $L = \|\hat{\mathbf{l}}'(t) - \hat{\mathbf{l}}(t)\|_2$, where the predicted position is $\hat{\mathbf{l}}'(t) = \mathbf{H}\hat{\mathbf{x}}'(t)$. In the process of the tracking, we consider the reward consisting of both the tracking accuracy and the energy consumption in each time slot given as follows.
 - a) *Tracking Accuracy*: For quantifying the tracking accuracy to measure the tracking effect of WSNs, classical

measurement (such as estimation error covariance) represents the error between $\hat{\mathbf{l}}'(t)$ and $\hat{\mathbf{l}}(t)$, but we would like to measure the error between $n_s(t)$ and $n_a(t)$, which depends on $\hat{\mathbf{l}}'(t)$ and $r_a(t)$. By adopting $S_{\text{int}}(t) = n_s(t) \cap n_a(t)$ as the metric, we can measure the effect of $r_a(t)$ on energy consumption and track accuracy. As such, $\hat{\mathbf{l}}'(t) = \hat{\mathbf{l}}(t)$ satisfies when $L = 0$ and $\max[r_a(t)] = r_s$; thus, as $S_{\text{int}}(t)$ increases, the predicted position becomes more accurate. We define $S_{\text{int}}(t) = r_a^2(t)[\theta_1(t) - \sin], \theta_1(t)\cos\theta_1(t)] + r_s^2[\theta_2(t) - \sin\theta_2(t)\cos\theta_2(t)]$. Herein, $\theta_1(t)$ and $\theta_2(t)$ are the angles of intersection area, which are obtained by $\theta_1(t) = \cos^{-1} \frac{r_a^2(t)+L^2-r_s^2}{2r_a(t)L}$ and $\theta_2(t) = \cos^{-1} \frac{r_s^2+L^2-r_a^2(t)}{2r_sL}$, respectively.

- b) *Energy Consumption*: In duration of $\tau(t)$, the energy consumption generated by data transmission is

$$e_{\text{com}}(t) = P_t \sum_{i=1}^{|m(t)|} \tau_i^t(t) + P_r \tau_2^r(t) + P_l \sum_{j=1}^{|m(t)|-1} \tau_2^j(t) + P_t \tau_3^t(t) + P_r \sum_{k=1}^{|m_a(t+1)|} \tau_3^k(t) \quad (4)$$

where P_t and P_r denote the powers of nodes for transmitting and receiving data, respectively. In addition, the energy consumption of nodes for waking up in $n_a(t)$ and working in $m(t)$ is $e_w(t) = [P_w|m(t)| + P_{\text{idle}}(|m_a(t)| - |m(t)|)]\tau(t)$, where $|m_a(t)|$ denote the amount of sensors of $n_a(t)$, the power of the nodes in working mode is denoted as P_w , and the power of the nodes in idle mode is denoted as P_{idle} [5]. Thus, the total energy consumption is $e(t) = e_{\text{com}}(t) + e_w(t)$.

Therefore, as the goal of this system is to improve the tracking accuracy and to minimize the energy consumption, we can define reward $R(t)$ by combining normalized $S_{\text{int}}(t)$ and $e(t)$ as $R(t) = \frac{S_{\text{int}}(t)}{\pi r_s^2} - \frac{e(t)}{e_{\text{max}}}$, where e_{max} denotes the maximum energy consumption in each time duration.

It is noteworthy that, as the number of the training episodes increases, there may exist a certain degree of disturbance in the total rewards in a single episode; thus, the increase of the total rewards in a single episode does not represent an accurate improvement of the system performance. Therefore, our goal is to find an optimal policy π^* with the maximum average total reward given by

$$\pi^* = \arg \max \frac{\sum_{t=1}^T R(t)}{T}. \quad (5)$$

IV. PROPOSED DRL-BASED METHODS

In this section, to solve the problem (5), we adopt the policy iteration based DDPG method and the value iteration based DQN method. Additionally, in the DQN method, we use the action selection strategy of “softmax” to compare with the “greedy” strategy.

A. Proposed DDPG-Based Method

The DDPG method is an algorithm that combines the actor-critic framework and the neural network[10], where the actor-critic learns both the policy and value network. In DDPG, when the state and action value are the input of a Q -function, it estimates a Q -value $Q^\pi(s, a)$ according to a policy π as $Q^\pi(s, a) \leftarrow \mathbb{E}_s[r + \gamma \max_{a'} Q^\pi(s', a') | s, a]$, where s and a are the current state and action, s' and a' are the next state and action, and $\gamma \in [0, 1]$ is a discount factor to the future reward.

Algorithm 1 DQN Based Dynamic Activation Area Adjustment Scheme

- 1: Initialize ϑ and $\bar{\vartheta}$; r and q ; \mathcal{D} and N_t ; ι and $T = 0$;
- 2: **for** episode $\ell = 1, N_t$ **do** (N_t is the number of episodes)
- 3: Get the initial state s_1 ;
- 4: **while** the vehicle under tracking **do**
- 5: Choose action based on ε -greedy policy or softmax policy;
- 6: Obtain reward r and store (s, a, r, s') in \mathcal{D} ;
- 7: **if** the memory \mathcal{D} is full **then**
- 8: Sample mini-batch K randomly from \mathcal{D} ;
- 9: $\vartheta \leftarrow \min_{\vartheta} l(\vartheta)$ and every E steps reset $\bar{Q} = Q$;
- 10: **end if**
- 11: Set $T = T + \tau(t)$, return q ;
- 12: **end while**
- 13: **end for**

The policy network is termed as the actor, and the value network is termed as the critic. In DDPG, the critic receives (s, r) and produces a temporal-difference (TD) error $\sigma = r + \gamma Q(s', a') - Q(s, a)$. With a TD error, the actor network updates with the direction suggested by the critic network. In a DDPG-based algorithm, for avoiding the influence of data correlation in training, the actor network is divided into a current actor network $\mu(s|\vartheta^\mu)$ and a target actor network $\mu'(s|\vartheta^{\mu'})$, whereas the critic network is divided into the current critic network $Q(s, a|\vartheta^Q)$ and the target critic network $Q'(s, a|\vartheta^{Q'})$. The weights of four NNs will be updated as $\vartheta^{Q'} \leftarrow \iota \vartheta^{Q'} + (1 - \iota) \vartheta^{Q'}$ and $\vartheta^{\mu'} \leftarrow \iota \vartheta^{\mu'} + (1 - \iota) \vartheta^{\mu'}$, where ι is the learning decrement.

B. Proposed DQN-Based Method

This letter considers two action selection methods.

- 1) *ε -Greedy Policy*: In each time slot, action selection according to $a' = \arg \max_a Q(s, a; \vartheta)$ when $\psi_t < \varepsilon$ and ψ_t is a random variable. Then, select a randomly in \mathcal{A} . At the end of each episode, the parameter ε will be updated by $\varepsilon = \max\{\varepsilon_{\text{min}}, \varepsilon - \zeta\}$, where ε_{min} is the minimum for ε , and ζ is the decrease speed.
- 2) *Softmax Policy*: For getting the selection probability $P(a)$ of action a , the softmax-based action selection policy is formulated as $P(a) = (e^{\frac{1}{2} \sum_1 r(a)}) / (\sum_{i=1}^{\text{card}(\mathcal{A})} e^{\frac{1}{2} \sum_1 r(a_i)})$, where $r(a)$ is the reward based on action a , and $r(a_i)$ is the reward based on current action a_i .

Additionally, DQN employs the two networks with the same structure but different parameters ϑ and $\bar{\vartheta}$, respectively. For training the model, we search the weights by minimizing the loss function $\min_{\vartheta} l(\vartheta) = \sum_{t=0}^T [\hat{Q}(s, a; \vartheta) - y_t^{\text{DQN}}]^2$, where $y_t^{\text{DQN}} = r_t + \gamma \max_{a'} \hat{Q}(s', a'; \bar{\vartheta})$, $\hat{Q}(s, a; \vartheta)$ represents a predicted maximum Q -value with weight ϑ , and y_t^{DQN} represents the target Q -value with weight $\bar{\vartheta}$. The details of this process are shown in Algorithm 1.

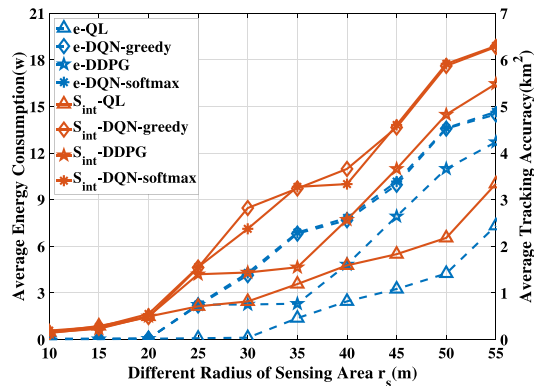
V. SIMULATIONS AND RESULTS

Based on the previous research in [7], we consider the field of WSNs is $360 \times 600 \text{ m}^2$. Besides, the motion model is

$$\mathbf{x}(t+1) = \begin{bmatrix} 1 & \tau & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & \tau \\ 0 & 0 & 0 & 1 \end{bmatrix} \mathbf{x}(t) + \begin{bmatrix} \frac{\tau^2}{2} & 0 \\ \tau & 0 \\ 0 & \frac{\tau^2}{2} \\ 0 & \tau \end{bmatrix} \begin{bmatrix} w_x(t) \\ w_y(t) \end{bmatrix} \quad (6)$$

Table 1. Simulation Parameters.

parameter	value	parameter	value	parameter	value
B (MHz)	1	N_b (bits)	2×10^4	P_w (W)	5
P_{idle} (W)	0.05	γ	0.9	\mathcal{D}	2000
N_i	1800	ϑ	0.5	E	500
K	30	ε	0.9	ι'	0.01
ϑ^μ	0.5	ϑ^Q	0.5	$\vartheta^{\mu'}$	0.5
$\vartheta^{Q'}$	0.5	$\bar{\vartheta}$	0.5	σ^2 (dBm)	-110

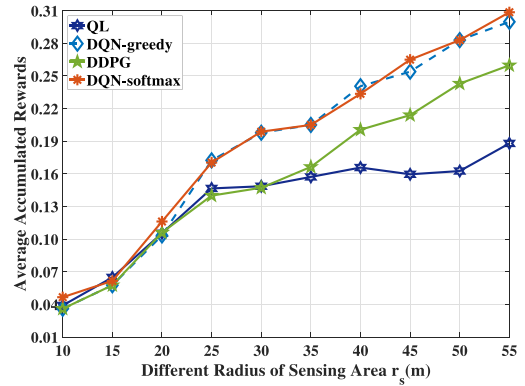
Fig. 2. Energy consumption and tracking accuracy versus r_s .

where $\mathbf{x}(t)$ is the vector of the vehicle, $\tau = \tau(t)$ is the length of each time interval, and $w(t)$ is the vector noise. The initial vector is $\mathbf{x}(0) = [0 \ 7.84 \ 0 \ 7.84]^T$, which means that the initial speed is 40 km/h. The vector noise accounting for the unpredictable modeling error is characterized by $\mathbf{Q} = \mathbb{E}[\mathbf{w}(t)\mathbf{w}^T(t)] = \begin{bmatrix} 0.03 & 0 \\ 0 & 0.03 \end{bmatrix}$.

In the tracking of a single vehicle, there are many sensors that can be used in the scenario, such as cameras [5] and logical combination of ranging sensors [2]. By adopting the strategy of uniform distribution of sensor nodes in [5], we set 375 nodes in the sensing range with the density of 1 sensor/24 m, and the linear measurement model of each sensor is $\mathbf{z}_i(t) = \mathbf{H}\mathbf{x}(t) + \begin{bmatrix} v_x(t) \\ v_y(t) \end{bmatrix}_i$, where $\mathbf{H} = \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 \end{bmatrix}$. Notably, the motion model can also be a nonlinear model, which can be estimated by an extended Kalman filter, a particle filter, or other methods. The parameters of the measurement noise covariance are $\mathbf{R}_i = \mathbb{E} \left[\begin{pmatrix} v_x(t) \\ v_y(t) \end{pmatrix}_i \begin{pmatrix} v_x(t) \\ v_y(t) \end{pmatrix}_i^T \right] = \begin{pmatrix} 400 & 0 \\ 0 & 400 \end{pmatrix}$. We randomly initialize $\mathbf{x}(0)$, and the parameters used in this model are shown in Table 1.

Fig. 2 plots the trends of the average tracking accuracy $\frac{1}{T} \sum_{t=1}^T S_{int}(t)$ and the average energy consumption $\frac{1}{T} \sum_{t=1}^T e(t)$ with different r_s , where each value of $e(t)$ and $S_{int}(t)$ is the final convergence value obtained by training 1800 episodes. Clearly, increasing sensing area $n_s(t)$ achieves higher $S_{int}(t)$ and $e(t)$.

Fig. 3 shows the average accumulated rewards $\frac{1}{T} \sum_{t=1}^T R(t)$ of the proposed algorithms. First, we can observe that although $e(t)$ and $S_{int}(t)$ increase with r_s , their gaps in terms of the average accumulated rewards enlarge gradually. Second, as episodes go by, the average accumulated rewards based on DQN is much higher than other methods. The reasons include two aspects: First, the QL-based method leads to the lowest value because of the Q -Table has a limited capacity, and second, the value iteration of DQN is based on the unbiased estimation of data, whereas the DDPG is based on the biased estimation.

Fig. 3. Average accumulated rewards versus r_s .

VI. CONCLUSION

This letter focused on improving the tracking accuracy and energy saving of a target vehicle in WSNs. Thus, we proposed a decentralized vehicle tracking strategy, which dynamically adjusted the activation area to improve tracking accuracy and energy saving. Then, we defined the problem as the MDP and used the DRL method to solve it. Finally, the simulation results showed that the DQN-based method had a better performance than other DRL-based methods. In the future, we can explore multiagent DRL algorithms in a cooperative tracking scenario.

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