

# An Anti-jamming Game in VANET Platoon with Reinforcement Learning

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**Abstract--** This paper proposes a game strategy of anti-jamming power control-based Dyna-Q reinforcement learning to counter the smart jamming attacks suffered by the periodic beacons in Vehicular ad-hoc networks(VANETs) platoon. Simulation results indicate that without knowing the radio channel model of the jammer, the proposed algorithm can not only realize the vehicle maximize efficiency and improve the signal-to-interference-plus-noise(SINR) of radio channel but also attain better convergence effects compared with a Q-learning based scheme.

## INTRODUCTION

As a general mode of vehicle-to-vehicle (V2V) communication in VANETs, platoon can not only improve the road capacity and save energy but also improve the efficiency of traffic management[1]. In the platoon, IEEE802.11p is adopted to periodically update the beacon information about vehicle position and velocity in the dedicated channel. Thus the beacon is vulnerable to suffer jamming Denial-of-Service(DOS) attacks[2]. A smart jamming strategy presented in recent years can adjust its attack strategy in real time by learning the launch behavior of legitimate users, which makes it more difficult for VANETs to resist jamming[3].

## GAME MODEL

As shown in Fig.1, there are N smart vehicles and an intelligent jammer, and the smart vehicles are equipped with sensing devices, whereas the jammer can be a moving or stationary device. The N-smart vehicles are organized into a close-range platoon mode. To counter the smart jamming in VANETs platoon, the interaction between vehicles and jammer is formulated as the game model based on SINR and load overhead.

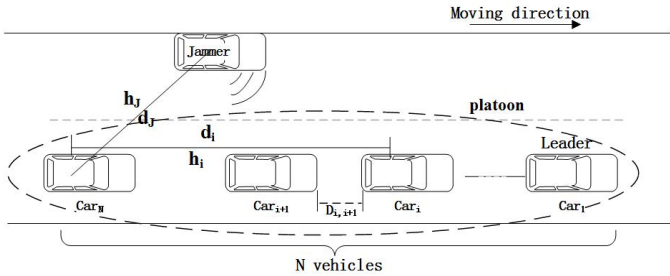


Fig.1 Network model

If CSMA/CA provides fair access to each vehicles, the time is divided into multiple slots and the vehicles are permitted to send beacons in slot  $k$ . In slot  $k$  vehicle  $i$  selects the transmit power to obtain a higher SINR with minimum load overhead. The corresponding channel gain is  $h_i$ , and load overhead of unit power is  $C_i$ . The utility of the vehicle is defined as follows:

$$u_i(x_i, y) = \frac{h_i x_i}{\sigma + h_j y} - C_i x_i \quad (1)$$

The jamming power selected by jammer  $J$  in slot  $k$  is  $y$ ,  $h_j$  denotes the corresponding channel gain, and  $C_j$  refers to the load overhead of unit power. The jammer aims to consume the energy of vehicle and block the ongoing transmission. The utility of it is defined as follows:

$$u_j(x_i, y) = -u_i - C_j y = -\frac{h_i x_i}{\sigma + h_j y} + C_i x_i - C_j y \quad (2)$$

## THE ALGORITHMS

To obtain the optimal transmit power of dynamic jamming game in VANETs platoon, Dyna-Q learning [4] is introduced to control the power of VANETs and obtain the optimal utility by means of historic study.

Vehicle  $i$  can iteratively update the vehicle's value function  $Q_i(s_i, x_i)$  as the learning deepens.  $V_i(s_i^k)$  means that the vehicle node  $i$  in a certain state  $s_i^k$  can obtain the maximum  $Q_i(s_i, x_i)$  by selecting the effective transmit power.  $V_i(s_i^k)$  and  $Q_i(s_i, x_i)$  can be separately updated by using the following formulas:

$$Q(s_i^k, x_i^k) = (1 - \alpha)Q_i(s_i^k, x_i^k) + \alpha(u_i(x_i^k, y^k) + \delta V_i(s_i^{k+1})) \quad (3)$$

$$V_i(s_i^k) = \max_{x_i \in X} Q_i(s_i^k, x_i) \quad (4)$$

It also should build the real experience record for each action - state pair and formulate the environment model. The experience in every slot  $k$  includes  $\langle s_i^k, x_i^k, u_i^k, s_i^{k+1} \rangle$ , which refers to the utility  $s_i^k$  attained by vehicle  $i$  in the state of  $s_i^k$  by selecting transmit power  $x_i^k$ , and then vehicle  $i$  transfers to the next state  $s_i^{k+1}$ . With accumulation of interaction experience, the environmental model can approximate the state transfer probability function  $\Pi(s_i^k, x_i^k, s_i^{k+1})$  and utility function  $\tau_i(s_i^k, x_i^k)$  of the real environment. The above two functions can be updated as follows:

$$\Pi(s_i^k, x_i^k, s_i^{k+1}) = \frac{H_i'(s_i^k, x_i^k, s_i^{k+1})}{H_i(s_i^k, x_i^k)} \quad (5)$$

$$\tau_i(s_i^k, x_i^k) = \frac{1}{H_i(s_i^k, x_i^k)} u_i + \frac{H_i(s_i^k, x_i^k) - 1}{H_i(s_i^k, x_i^k)} \tau_i(s_i^k, x_i^k) \quad (6)$$

$H_i(s_i^k, x_i^k)$  stands for the real number of transmit power  $x_i^k$  in state  $s_i^k$ , and the real number of state  $s_i^{k+1}$  is expressed as  $H_i'(s_i^k, x_i^k, s_i^{k+1})$ . The utility function is attained by calculating the mean approximation utility of the same action - state pair.

With the help of the existing environment model, vehicle node  $i$  can generate  $E$  simulation experiences and update function  $Q$ . The state-action pair  $(\hat{s}_i^e, x_i^e)$  is selected randomly and the next state  $\hat{s}_i^{e+1}$  is attained according to  $\Pi_i$ . Function  $Q$  should be updated based on the following two formulas:

$$Q_i(\hat{s}_i^e, x_i^e) = (1 - \alpha)Q_i(\hat{s}_i^e, x_i^e) + \alpha(\tau_i(\hat{s}_i^e, x_i^e) + \delta V_i(\hat{s}_i^{e+1})) \quad (7)$$

$$V_i(\hat{s}_i^e) = \max_{x_i \in X} Q_i(\hat{s}_i^e, x_i) \quad (8)$$

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**Algorithm 1.** Power control strategy based on Dyna-Q.

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Initialized  $Q, V, \alpha, \delta, E, \Pi, \tau_i$ ;

for  $k=1, 2, 3, \dots$

Detect the current state  $s_i^k = [h_i^k, y^{i-1}]$  and selects transmit power  $x_i^k$  with  $\varepsilon$ ;

Obtain new state  $s_i^{k+1}$  and utility  $u_i^k$ ;

Update  $Q_i(s_i^k, x_i^k)$  and  $V_i(s_i^k)$  via (3) and (4);

Record the real experience  $\langle s_i^k, x_i^k, u_i^k, s_i^{k+1} \rangle$ , then update the state transfer probability  $\Pi(s_i^k, x_i^k, s_i^{k+1})$  and utility  $\tau_i(s_i^k, x_i^k)$  via(5) and (6);

for  $e=1$  to  $E$  do

Select state-action pair  $(\hat{s}_i^e, x_i^e)$  randomly;

Got next state  $\hat{s}_i^{e+1}$  and utility  $u_i^k$ ;

Update  $Q$  of  $(\hat{s}_i^e, x_i^e)$  via (7) and (8);

End for

End for

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## SIMULATION RESULTS

To verify the effectiveness of the proposed anti-jamming game strategy, the paper also designs an anti-jamming strategy based on Q-learning, which mainly evaluates the changes in vehicle nodes utility and SINR of channels. If  $c_i = 0.01$ ,  $c_j = 0.01$  and  $\sigma = 0.5 \times 10^{-9}$ , the jammer selects its transmit power  $p_j$  according to the transmit power  $P_i$  of vehicle in the previous slot and the transmit power can be quantized as  $p_j = p_i = \{1, 3, \dots, 9\}$ ,  $i = 1, 2, 3$ . According to Fig.2, the convergence of the Dyna-Q strategy is superior to that of the Q-learning strategy. For example, the utility of a vehicle employing the Dyna-Q strategy in 200 slots is 0.1486, whereas the utility of the Q-learning strategy is 0.1316. During the

dynamic game process, the vehicle nodes adjust the transmit power to obtain the optimal utility and reduce the jamming of the jamming node via continuous learning. As shown in Fig.3, with increasing simulation slots, SINR of vehicle is improved continually and converges to the stable value; thus, the efficiency of the vehicle node to send information is improved. Meanwhile, the convergence of the SINR under the Dyna-Q strategy is superior to that of the Q-learning strategy.

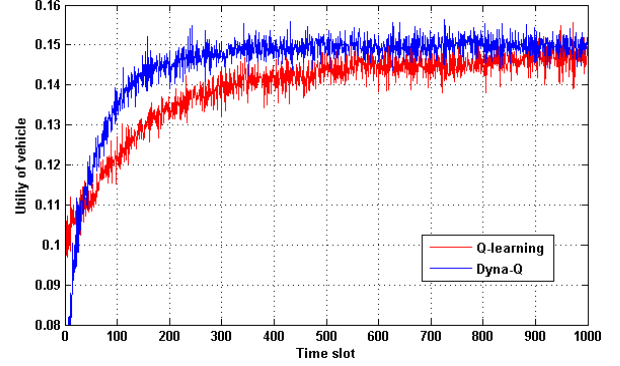


Fig. 2 Utility of vehicle

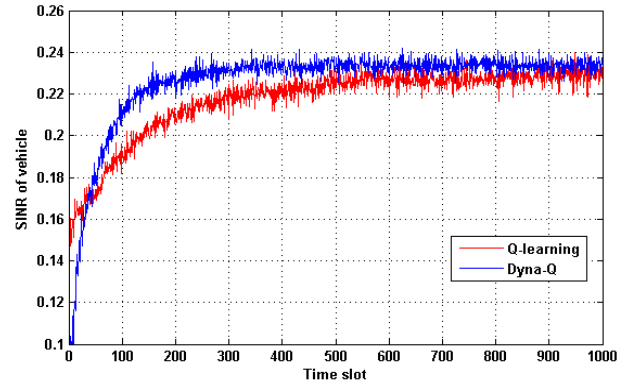


Fig. 3 SINR of vehicle

## CONCLUSION

In this paper, a power control game strategy of VANETs platoon is proposed to counter the smart jamming. With the help of the Dyna-Q learning method, the power control strategy is equipped with better anti-jamming and convergence performance. The simulation results indicate that the algorithm can not only obtain the optimum utility but also improve the SINR of the channel effectively.

## RERERENCES

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