UAV Relay in VANETs Against Smart Jamming With Deep Reinforcement Learning

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Abstract

Frequency hopping-based antijamming techniques are not always applicable in vehicular ad hoc networks (VANETs) due to the high mobility of onboard units (OBUs) and the largescale network topology. In this paper, we use unmanned aerial vehicles (UAVs) to relay the message of an OBU and improve the communication performance of VANETs against smart jammers that observe the ongoing OBU and UAV communication status and even induce the UAV to use a specific relay strategy and then attack it accordingly. On the basis of the latest technology hotbooting policy hill climbing-based UAV relay strategy, we use Deep Q-learning Network(DQN) to improve the convergence speed, and help the VANET resist jamming in the dynamic game without being aware of the VANET model and the jamming model. Our expected result is that the relay strategy improved by DQN is effective,and compared with the scheme based on Q learning, it reduces the bit error rate of OBU message, and makes the convergence speed faster when the performance is guaranteed, thus improving the utility of VANET.

1 Introduction

Vehicular ad-hoc networks (VANETs) support vehicle-to-vehicle communications and vehicle-to-infrastructure communications to improve the transmission security, help build unmanned-driving, and support booming applications of onboard units (OBUs)(Hartenstein and Laberteaux 2008). The high mobility of OBUs and the large-scale dynamic network with fixed roadside units (RSUs) make the VANET vulnerable to jamming(Azogu et al. 2013). A jammer sends faked or replayed signals and aims to block the ongoing transmissions between OBUs and the serving RSUs. By applying smart radio devices to observe the ongoing VANET communication and evaluate the underlying policy, a smart jammer not only has flexible control over the jamming frequencies and signal strengths but also induces the VANET to use a specific communication strategy and then attacks it accordingly.

The anti-jamming communication of VANETs can be significantly improved by using unmanned aerial vehicles (UAVs) to relay the OBU message. Being faster to deploy, UAVs generally have better channel states due to the line-of-sight (LOS) links and smaller path-loss exponents (Sedjelmaci, Senouci, and Ansari 2016; Zhou et al. 2015) when they communicate with OBUs and RSUs, compared with the serving RSUs at a fixed location on the ground that might be severely blocked by a smart jammer. Therefore, UAVs help relay the OBU message to improve the signal-to-interference-plus-noise-ratio (SINR) of the OBU signals, and thus reduce the bit-error-rate (BER) of the OBU message, especially if the serving RSUs are blocked by jammers and/or interference.

As a type of Deep Reinforcement Learning, the Deep Reinforcement Network(DQN) is realized to solve the problem that Q-learning and PHC-based relay strategy both need huge space to store the Q-table. More specifically, the DQN-based relay strategy can directly update strategy (i.e. the weights of netowrk) against smart jammer without knowing the jamming model. The contributions of this work can be summarized as follows:

- 1) We propose a DQN-based UAV relay strategy to resist smart jamming without the knowledge of the UAV channel model and the jamming model.
- 2) We simulate the system model in great detail, and reproduce Q-learning and PHC-based relay strategy. Simulation results show that this scheme achieves a lower BER of the OBU message and a higher utility compared with three benchmarks.

The rest of this paper is organized as follows. We review the related work in Section II and present the system model of the UAV-aided VANET in Section III. We introduce the DQN-based UAV relay strategy and compare it with other three benchmarks in Section IV. Experiment details and simulation results are provided in Section V and conclusion is drawn for this work in Section V.

2 Related Work

UAVs have been used to relay mobile messages for ground terminals. The optimization of multi-antenna UAVs andmobile ground terminals in (Zhan, Yu, and Swindlehurst 2011) improves the uplink sum rate in a wireless relay network.The UAV-aided intrusion detection scheme presented in (Sedjelmaci, Senouci, and Ansari 2016) uses UAVs to relay the alarm messages regarding lethal attacks of vehicles to improve the detection accuracy and reduce the energy consumption in vehicular networks.

The UAV placement strategy as developed in (Tuna et al. 2012) enhances the coverage of public safety communications. The UAV-aided sensor deployment in (Johansen et al. 2014) improves the localization and navigation to monitor post-disaster areas. The fifield tests in(Ueyama et al. 2014) show the impact of the UAV altitude on the communication quality in autonomous vehicles. The UAV-aided wireless sensor network as investigated in (Dong et al. 2014) can reduce the packet loss and power consumption of the network against node failures. The UAV-assisted data gathering system as developed in (Lu, Wang, and Wang 2013) reduces the required execution time and the energy consumption in wireless sensor networks. Those studies have shown that UAVs can improve the communication performance .

But it is a problem how to enhance jamming resistance the hideaway strategy as proposed in (Azogu et al. 2013) determines when to keep silent based on the packet transmission ratio to improve jamming resistance. The jamming detection scheme as proposed in (Benslimane and Nguyen-Minh 2016a) can improve the message invalidation ratio in time-critical networks. The MAC-based jamming detection scheme as presented in (Benslimane and Nguyen-Minh 2016b) reduces the false alarm rate and the time required to monitor vehicular networks.

Reinforcement learning techniques have been widely applied to improve security in wireless networks(Xiao et al. 2015; Bowling and Veloso 2001; Long et al. 2007). The noncooperative power control algorithm as presented in (Long et al. 2007) in the repeated game can improve the throughput of wireless ad hoc networks. The prospect theory based dynamic game as formulated in (Han, Xiao, and Poor 2017) shows the impact of the subjectivity of endusers and jammers on the throughput of cognitive radio networks with Q-learning algorithm. The deep Q-network algorithm as proposed in (Bowling and Veloso 2001) uses both frequency and spatial diverting to improve the SINR of the signals and the utility of the secondary user in cognitive radio networks.

3 UAV-AIDED VANETS

A. Network Model

In this work, we consider an OBU that moves along the road at a speed denoted by $v^{(k)} \in [0, \mathrm{V}]$at time slot k, where V is the maximum speed and time is partitioned into slots of a constant duration. The OBU aims to send a message to a server via several RSUs and a UAV in a time slot, as illustrated in Figure 1. The RSUs at fixed locations are connected via fibers with each other and the server. Equipped with sensors such as cameras and a global positioning system receiver, the OBU gathers the sensing information and sends a message to the server via the serving RSU denoted by RSU_1. We assume that both the UAV and RSU1 receive the message from the OBU and then the UAV decides whether to connect to the server via RSU_2 afterwards in the time slot. For simplicity, the constant channel power gains are assumed to be constant in each time slot.

Let $\mathbf{d}^{(k)} = \left[d_1^{(k)}, d_2^{(k)}, d_3^{(k)}, d_4^{(k)}, d_5^{(k)}\right]$ denote the typology vector of the network at time slot k, where $d_1^{(k)}$ denotes the distance denotes the distance between the OBU and RSU_1, $d_2^{(k)}$ is the distance between the OBU and the UAV, $d_3^{(k)}$ corresponds to the distance of the jammer-$\mathrm{RSU}_1 link$,$\mathrm{d}_4^{(k)}$ is the distance between the jammer and the UAV, and $d_5^{(k)}$ is the distance between the UAV and RSU_2. The distance $d_2^{(k)}$ and $d_1^{(k)}$ depend on the speed of the OBU at time slot k. The OBU sends a message to a server via RSU_1 and the UAV that is connected with RSU_2 at time slot k with a fixed transmit power $P^{(k)}$. The SINR of the signals received by γ(γ=1 for RSU_1 or γ=2 for the UAV) sent from the OBU and the SINR of the signals received by RSU_2 sent from the UAV at time slot k are denoted by$\rho_r^{(k)}$ and $\rho_3^{(k)}$,respectively. The BER of a signal denoted by $p_e(\rho)$ depends on SINR per bit,ρ of the received signal for a given modulation mode. The BER of the OBU message at time slot k denoted by $P_e^{(k)}$ depends on the OBU-RSU_1 link,the OBU-UAV link and the UAV-RSU_2 link, and is given by $P_e^{(k)} = \min\left(p_e\left(\rho_1^{(k)}\right), p_e\left(\min\left(\rho_2^{(k)}, \rho_3^{(k)}\right)\right)\right)$

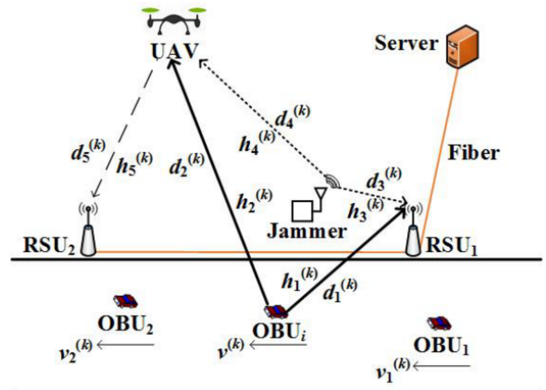

Figure 1: Illustration of a UAV-aided VANET, in which the OBU moving with speed v(k) sends a message at time slot k to a server via the serving RSU (RSU1) and the UAV that is connected with RSU2 and is less affected by the jammer.

The BER of the message depends on the minimum of the BER of the OBU-RSU_1 signal as shown in the first term, and the BER of the weaker signal of the OBU-UAV link and the UAV-RSU_2 link at that time as represented in the second term. According to the channel quality and the BER of the OBU message, the UAV decides whether or not to relay the OBU message to RSU_2, which is denoted by $x \in \mathbf{A} = \{0, 1\}$, where A is the feasible action set of the UAV. The UAV relays the OBU message at time slot k with a fixed transmit power $P_U^{(k)}$ and a transmat energy cost $C_U^{(k)}$ if x = 1, and keeps silent otherwise. The system server can gather the sensing message sent from the OBU via RSU_1 or the UAV.

The smart jammer applies smart radio devices to eavesdrop the control channel of the VANET and estimated the VANET transmission policy.According to the estimated VANET communication, the smart jammer changes its jamming power $y \in \left[0, P_J^M\right]$ where P_J^M is the maximum jamming power. For simplicity, we assume a constant noise power in the received signal denoted by σ and the jammer is too far away from the UAV and RSU_2 to block them.

B. Channel Model

The channel power gain vector of the system denoted by$\mathbf{h}^{(k)} = \left[h_1^{(k)}, h_2^{(k)}, h_3^{(k)}, h_4^{(k)}, h_5^{(k)}\right]$at time slot k consists of the channel power gain of the OBU-RSU_1 link $h_1^{(k)}$, the OBU-UAV $h_2^{(k)}$, the jammer-RSU_1 link $h_3^{(k)}$, the jammer-UAV link $h_4^{(k)}$, and the UAV-RSU_2 link $h_5^{(k)}$. Similar to [19], the channel gain is modeled as $h_i^{(k)} = \theta_0 \Delta_i^{(k)} \left(\frac{d_i^{(k)}}{d_0}\right)^{-\alpha_i}$ where θ_0 is the channel power gain at the reference distance d_0, the channel time variation$\Delta_{\mathrm{i}}^{(\mathrm{k})}$ depends on the Doppler shift due to the node mobility. The path-loss exponent α_i is set according to (Erceg et al. 1999) and (Palat, Annamalau, and Reed 2005), e.g.,α_i=2 for the OBU-UAV, jammer-UAV and UAV-RSU_2 links and α_i = 4 otherwise. The path loss of the jammer-UAV radio link is assumed to be much higher than that of the jammer-RSU_1 link due to a longer distance. Similarly, the radio link between the OBU and the UAV has a higher path loss compared with that of the OBU-RSU_1 link.

Due to the uncorrelated locations of RSU_1 and the UAV, $h_1^{(k)}$ is independent with $h_2^{(k)}$. The UAV transmission fails if the UAV is too far away from the OBU, and the UAV can cover the whole geographic area if it is high enough. For simplicity, the channel power gain is quantized into N levels with $h_i^{(k)} \in \{H_a\}_{1 \leq a \leq N}, i = 1, 2$, and is modeled as a Markov chain with N states. As shown in Figure 2, the transition probability of the channel gain hi from H_m to H_n during time slot k denoted by $P_{i,m,n}^{(k)}$ depends on the OBU speed given by $p_{i,m,n}^{(k)} = \Pr\left(h_i^{(k)} = H_n \mid h_i^{(k-1)} = H_m\right)$.

4 Proposed Solution

The repeated interactions between the UAV and the smart jammer in the VANET can be formulated as a dynamic game, in which the jammer determines its jamming power based on the previous VANET transmission, and the UAV chooses its relay strategy based on the system state, which consists of the radio channel state and the BER of the OBU message observed in last time slot. Therefore, the UAV relay process in the dynamic game can be viewed as an MDP and the UAV can apply reinforcement learning techniques such as PHC to derive its optimal strategy via trials without the knowledge of jamming model. In the dynamic game, the UAV decides whether or not to relay the OBU message based on the system state at time slot k denoted by s(k) that consists of the link quality between the UAV and the OBU, that between RSU_1 and the OBU, the SINR between RSU_2 and the UAV, and the BER of the OBU message at the previous time slot, i.e.,

$$\mathbf{s}^{(k)} = \left[\rho_1^{(k-1)}, \rho_2^{(k-1)}, \rho_3^{(k-1)}, P_e^{(k-1)}\right]$$

The Q-function of the action x at state s is denoted by Q(s, x) and is updated in each time slot according to iterative Bellman equation as follows:

$$\begin{aligned} Q(\mathbf{s}, x) \leftarrow & (1-\alpha) Q(\mathbf{s}, x) \\ & + \alpha \left(u_U(\mathbf{s}, x) + \delta V\left(\mathbf{s}'\right)\right) \end{aligned}$$

where s‘ is the next state if the UAV chooses x at state s, and the value function V(s) maximizes Q(s,x) over the UAV action set given by

$$V(\mathrm{s}) \leftarrow \max_{x \in \{0,1\}} Q(\mathrm{s}, x)$$

In addition, the mixed-strategy table in the PHC-based relay denoted by (s, x) is updated by increasing the probability corresponding to the highest valued action by $\beta \in (0, 1]$, and decreasing other probabilities by$-\beta/(|A| - 1)$, i.e.,

$$\begin{aligned} \pi(\mathrm{s}, x) \leftarrow & \pi(\mathrm{s}, x) \\ & + \begin{cases} \beta, & x = \max_{\hat{x} \in \{0,1\}} Q(\mathrm{~s}, \hat{x}) \\ \frac{-\beta}{|\mathrm{A}|-1}, & \text{o.w.} \end{cases} \end{aligned}$$

The UAV then selects whether or not to relay the OBU message $x \in A$ according to the mixed strategy(s, x), i.e., $\Pr\left(x = x^*\right) = \pi\left(\mathbf{s}, x^*\right), x^* \in \mathbf{A}$

However, both Q-learning and PHC Based relay are non-deep learning algorithm which need huge space to store the Q-table. Further, it would be difficult to converge if the action-space and the state-space become large. In our system model, the action-space has only 0 and 1 to denote whether or not to relay the message from OBU. But the state space is a four-dimensional continuous tensor, and in the first three algorithms we can only approximate state values by discrete values, but DQN can extract features from continuous states. Therefore, in theory, the efficiency and convergence speed of Q and PHC are better than that of non-depth. Deep Q Network (DQN) uses deep neural network to estimate the action-value function. $Q_\pi(s, a; \theta) \approx Q_\pi^*(s, a)$

Now,the estimated and real Q-value becomes an estimated value: $Q_\pi\left(s_t, a_t; \theta\right)$ and a real value:

$$R_{t+1} + \gamma \max_a Q\left(s_{t+1}, a; \theta\right).$$

And, we use gradient decent to update the Q value,

$$\nabla_\theta L_t = E\left[R_{t+1} + \gamma \max_a Q\left(s_{t+1}, a; \theta\right) - Q_\pi\left(s_t, a_t; \theta\right)\right]$$

In this way,the DQN based relay strategy gives the action choice and learns the jamming strategy in the anti-jamming transmission dynamic game against smart jammer and achieves the optimal relay strategy to improve the long-term anti-jamming transmission performance.

5 Experiments

Simulations have been performed to evaluate the performance of the proposed UAV relay strategy in the dynamic game against smart jamming. In the simulations, the jammer was stationary and observed the ongoing VANET communication. The jammer applied greedy strategy to choose the jamming power regarding the expected reward uj in (5) during the VANET communication in each time slot. The radio link between the jammer and RSU2 was much worse than that between the jammer and RSU1 due to a longer distance, which leads to a lower channel gain. In this simulation experiment, we set P = 10, $P_U = 2, C_U = 1, C_J = 0.5, = 0.1, h_3 = 0.4, h_4 = 0.2, h_5 = 0.5$,$h_1$ in the range of [0.2,0.6] and h_2 in the range of [0.6,0.8]. More specifically, the transmit power of the UAV was (X) times higher than that of the OBU, with a unit relay energy cost. The jammer had a lower channel gain to the UAV than RSU1 due to a longer distance. Similar to the channel model in [33], the Doppler shift was considered in the OBU-RSU1 and OBU-UAV channel models. The channel gain transition probability linearly increases with the moving speed of the OBU, and is given by:

$$p_{i,m,n}^{(k)} = \begin{cases} \frac{\varphi v^{(k)}}{V}, & \text{if } (m,n) = (1,2) \text{ or } (N, N-1) \\ 1 - \frac{\varphi v^{(k)}}{V}, & \text{if } 1 \leq m = n \leq N \\ \frac{\varphi v^{(k)}}{2V}, & \text{if } 2 \leq m \leq N-1 \text{ and } n = m \pm 1 \\ 0, & \text{otherwise} \end{cases} \tag{1}$$

Where φ denotes the impact of the environmental changes.We set the Vmax = 5,and the $\varphi = 0.9$. Through reading the literature, we reproduce three algorithms of this task in the literature:

1. Q-learning-based relay; 2. the PHC-based relay; 3. The hotbooting PHC-based relay;

In addition to the above three existing algorithms, we also introduce a new DQN algorithm.In non-deep Q and PHC, we index the Q table with discrete state values, but in DQN, we directly take state sinr as the network input. Relu is used as the activation function of the hidden layer. Use Adam as the optimizer. Eval-network is updated in each time-slot and target-network is updated every 50 epochs to synchronize its weights with eval-network.Limited by the two-dimensional action space, the decision of the whole intermediate problem is relatively simple. Theoretically, there will be no problems such as fitting, because it is not considered in the initial implementation, and the subsequent simulation results prove that it does not occur.The results of the four algorithms are shown in the Figure 2,Figure 3 and Figure 4 :

Algorithm 1: DQN Based UAV relay strategy.

Initialize α, s (0), A, Target-net, Eval-net
for k=1,2,3, . . ., K **do**
  Choose $x^{(k)} \in A$
  if $x^{(k)} = 1$ **then**
    Relay the OBU message to RSU2 with a fixed transmit power $P_U{}^{(k)}$
  end if
  Collect SINR $\rho 1$,$\rho 2$,$\rho 3$ and BER Pe from server
  Obtain utility $u_U{}^{(k)}$
  $s^{(k+1)} = [\rho_1{}^{(k)}, \rho_2{}^{(k)}, \rho_3{}^{(k)}, P_e{}^{(k)}]$
  Feed [$s^{(k)}$, $x^{(k)}$, $u_U{}^{(k)}$, $s^{(k+1)}$] to Replay Buffer
  Update Eval-net
  if step mod 2 = 0 **then**
    Update Target-net with Eval-net
  end if
end for=0

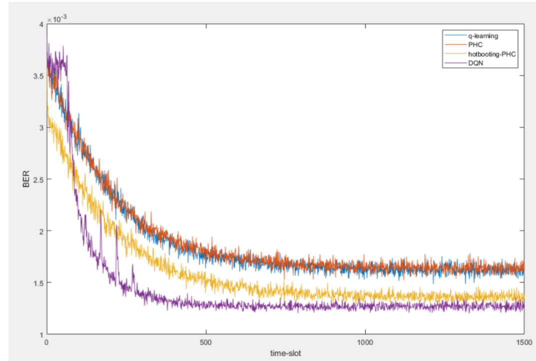

Figure 2: Y-coordinate: BER, X-coordinate: epoch.

As shown in the Figure 3,the BER of the OBU message of the DQN-based decreases with time, e.g., from 4‰ at the beginning of the game to 1.2‰ after 1500 time slots, which is about 33% lower than that of the Q-learning based and PHC based. This is because the DQN-based relay strategy can take continuous SNR as parameters for adversarial learning and has much larger parameter space than PHC.The utilization of uAVs has been significantly improved.

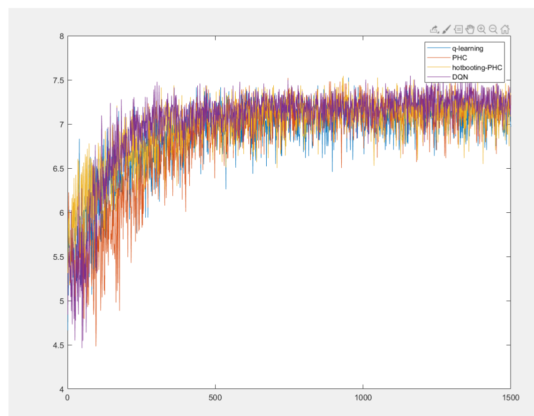

Figure 3: Y-coordinate: utility, X-coordinate: epoch.

In the DQN algorithm, we directly feed the calculated SINR back to the model for decision making, rather than using a discrete value to approximate the real SINR like Q-Learning, PHC and hot-PHC algorithms.In Figure 3, due to the small Epochs, the advantages of DQN over the other three algorithms are not obvious.This may be because there are only two decision states in the simulation experiment, which greatly limits the performance of the DQN algorithm.And with the increase of EPOCH, DQN has more obvious advantages over the other three algorithms.

In Figure 4, with the increase of Epoch, DQN has more obvious advantages than the other three algorithms.Compared with the previous three algorithms, DQN algorithm can obviously realize convergence in a shorter time, and its effect is slightly improved.As can be seen from the pseudo-code, the learning process of DQN is to package the past [state, action, benefit utility, subsequent state]

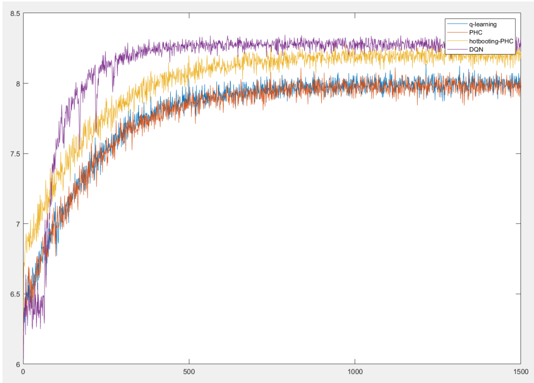

Figure 4: Y-coordinate: utility, X-coordinate: epoch.

into replay-buffer, and then randomly sample it each time.So DQN doesn't start learning until the replay-uffer fills up for the first time, so it starts a little later than other algorithms.As shown in the Figure 4.

6 Conclusion

In this report, based on the mature VANET communication anti-jamming model, we deeply simulated the actual model scene in detail. Firstly, we reproduced Q-learning and PHC algorithms as benchmark, and finally realized the UAV relay strategy based on DQN. So that the UAV has the ability to assist OBU to resist interference when the jamming model of intelligent jammer is unknown.Through simulation, we prove that DQN is better than benchmark in reward, BER and convergence speed. In a small training period, DQN algorithm is limited to only two possible action Spaces, and its performance advantage is not obvious. After a long training period, DQN shows better convergence speed and lower bit error rate.

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