Journal of Ambient Intelligence and Humanized Computing (2022) 13:1307–1319
https://doi.org/10.1007/s12652-020-02575-x

ORIGINAL RESEARCH

Research on adaptive beacon message transmission power in VANETs

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Received: 5 June 2020 / Accepted: 22 September 2020 / Published online: 30 September 2020

Abstract

In the future vehicular ad hoc networks (VANETs), vehicles communicate by sending beacon messages. However, fixed-period beacon messages cannot adapt to the characteristics of fast vehicle speed and variable network topology, and may contend for channel failure when there are many vehicles, resulting in the relevant information not being able to be known to surrounding vehicles, increasing the possibility of danger. In order to solve this problem, this paper proposes an adaptive beacon transmission power algorithm based on vehicle position prediction error, which increases the beacon transmission power of vehicles with large vehicle position prediction errors and reduces the transmission power of vehicles with small errors. And analyze the relevant factors that may affect the results in the experiment, and formulate relevant solutions to signal fading and channel contention. Finally, the experimental results show that, compared with the fixed transmit power, the proposed adaptive power reduces the CBT by about 16% and improves the packet transmission rate by about 4.5%, ensuring the effective transmission of security information.

Keywords Vehicular ad hoc networks (VANETs) · V2V communication · Linear combination model · Adaptive transmission power · Signal weakness · Channel contention

1 Introduction

In recent years, with the increasing number of vehicles, road traffic accidents have also increased, seriously affecting people's lives and property safety. In order to improve the current traffic environment, the vehicular ad-hoc networks (VANETs) came into being. It is the most promising method for future intelligent transportation system (ITS) to improve traffic efficiency and traffic safety (Shah et al. 2016; Sulistyo and Alam 2018). Internet of vehicles (IoV) is the future road traffic system model (Fig. 1). Through information sharing between vehicles, road traffic accidents are reduced, road traffic safety is improved, and people's lives and property are protected (Jiang et al. 2020a, b, c; Egea-Lopez and Pavon-Marino 2016).

Messages related to vehicle active safety applications in IoV are divided into periodic Beacon messages and Warning messages triggered by emergency events (Fallah et al. 2010a, b). The content of Beacon message includes speed, location and driving direction. The neighboring vehicle nodes of the surroundings broadcast the beacon message of the vehicle to understand the distribution of the surrounding vehicles in advance to avoid the occurrence of traffic accidents (Kwon and Rhee 2016; Jiang et al. 2020a, b, c). The Warning message is a multi-hop broadcast message. It is sent in case of accident or congestion, which is sudden. The source node vehicle needs to broadcast warning messages to other vehicles within the communication range in a timely and reliable manner. Because the spread of warning messages is based on beacon messages, its priority is higher than beacon messages.

The main performance indicators of beacon message broadcasting are fast, efficient and reliable (Dong et al. 2017). Therefore, real-time and effective beacon message transmission is the basis of all other services in the vehicle's self-organizing network. However, due to the characteristics of the fast change of the topology of the vehicle nodes in the internet of vehicles and the easy disconnection of the communication link, the stable transmission of beacon messages becomes very difficult (Bouk et al. 2015). When the vehicle density is large, if the beacon message sent according to the traditional mechanism may cause channel congestion, the packet loss rate of the beacon message in the

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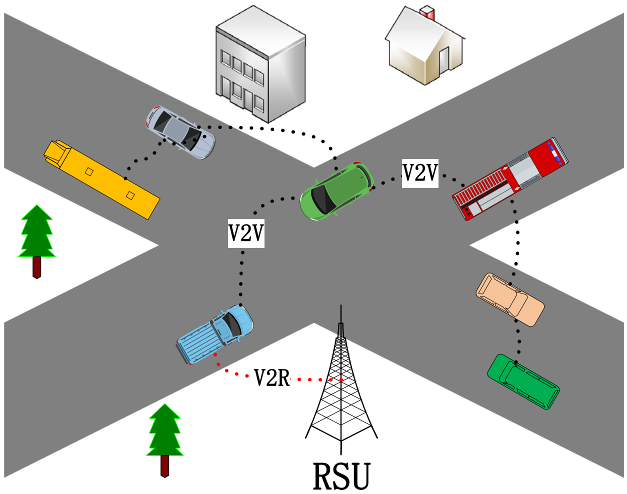


Fig. 1 Internet of vehicles

network is increased. However, when the vehicle density is low, if a beacon message is sent according to the traditional mechanism, it may cause unnecessary waste of channel resources. From the relevant research shows that (see Sect. 2 for details), the adaptive control of beacon message transmission power can improve the real-time and effectiveness of beacon message.

The rest of the article is organized as follows. Section 2 presents some related research on the transmission power control of beacon messages. In Sect. 3, we use a linear combination model to reduce vehicle turning errors and introduce an adaptive beacon message transmission control algorithm. In Sect. 4, we analyze the factors that may affect the experiment and propose corresponding countermeasures. Section 5 introduces the experimental simulation parameter setting and result analysis. Section 6 summarizes the paper and introduces future work.

2 Related work

Many scholars adjust the transmission power of beacon message to solve the problem of channel congestion. The related research includes:

Ali Shah et al. (2018) proposed a multi-metric power control (MPC) method, which uses application requirements and channel status to determine the transmit power of safety messages. MPC will try its best to meet the coverage of messages specified by the application according to its own situation. Also, it will give different message types with different coverage to control congestion, thereby improving cognition by minimizing beacon collisions. The performance analysis of MPC using discrete event simulation verifies the importance of MPC in improving reliability and reducing collisions under different vehicle densities. However, the accuracy of the application requirement range calculated by the algorithm cannot be measured.

Egea-Lopez et al. (2013) proposed a new statistical method for statistical beacon congestion control, which is used for transmit power control (TPC), which is called statistical beaconing congestion control (SBCC). SBCC uses local information and very limited feedback, and its implementation is simple. Each vehicle calculates the power required to meet a given maximum beacon load based on the estimated channel parameters, vehicle density, and beacon rate. Experimental results show that this method can effectively control beacon blocking.

In Xu et al. (2016) proposed a VANETs power control algorithm that can adapt to the change of traffic density. It constructs and updates the direct neighbor list by defining the power control cycle, adjusts the transmit power according to the position of the immediate neighbor vehicle, and then controls the coverage of the broadcast information of the node. Realize optimal allocation of channel resources. The experimental results show that the algorithm can reduce the channel occupancy and improve the packet delivery rate, but whether the adaptive algorithm can adapt to the changeable network topology remains to be studied.

Torrent-Moreno et al. (2009) proposed a distributed transmit power control method distributed fair power adjustment for vehicular environments (D-FPAV) based on strict fairness criteria for controlling the load of periodic messages on the channel. It provides bandwidth for higher priority data, such as issuing warnings; it also treats beacons from different vehicles equally, ensuring the best possible reception under the available bandwidth constraints. However, in traffic scenarios where vehicle density is very high, the performance of the vehicle-to-vehicle communication system is not ideal.

Shah et al. (2018) proposed an adaptive transmit power cooperative congestion control (AC3) method based on the cooperative game principle, which aims to allow vehicles to autonomously select their transmit power for their local channel congestion. And according to the number of neighbors of each vehicle and its corresponding change in transmission power, AC3 will make each vehicle reduce its transmission power fairly during congestion. Experimental results show that the method has the ability to determine reasonable power reduction for effective congestion control. However, this method needs to be verified in a real world environment.

Zemouri et al. (2018) proposed a prediction and adaptation algorithm (P and A-A), which is a new congestion control protocol that can perform joint adaptation of transmission rate and power based on the short-term prediction algorithm of the vehicle's altruism, And in a short time, given the density around the vehicle. In addition, P and A-A will ensure that the beacon sent meets most critical VANET applications to continuously adjust transmission parameters. Through simulation experiments, the results prove that it can significantly improve the network performance of IoV.

Zhou et al. (2019) proposed and analyzed a new power allocation strategy that uses amplified forwarding and hybrid decoded amplified forwarding amplify-and-forward and hybrid decode-amplify-forward (AF-HDAF) protocols, which can significantly reduce the power consumption of transportation systems The cooperative mode of the relay node of this strategy is based on the forward strategy of the cooperative node. In addition, according to the interruption probability constraints, the optimal power allocation to minimize the total power consumption is studied. Experimental results confirm the effectiveness of the power distribution scheme. However, the article does not give a solution for the case where the power distribution scheme cannot guarantee the total power consumption of the system.

Li et al. (2017a, b) aiming at the lag and inaccuracy of traditional power control, proposed an adaptive power control strategy based on fuzzy logic (FAPCS). The strategy first establishes a transmission range prediction model, predicts the transmission range that meets 90% of the packet delivery rate by predicting the traffic flow density value; then, designs the transmission for the impact of the hidden terminal and the predicted density error on the packet delivery rate Range adaptive adjustment model. Simulation results show that the control strategy can avoid channel congestion, make the packet delivery rate meet the needs of security-related applications, and have a faster convergence speed. However, the strategy of the article cannot maintain network connectivity when the vehicle density is low, cannot sense distant vehicles, and cannot guarantee the system throughput.

Mo et al. (2017) proposed a threshold-based IoV beacon transmission power control algorithm, which is to ensure the maximum connectivity of the network, preset the channel load threshold, specify a reasonable interval of channel load, and adjust the target node carrier detection range according to the threshold The beacon transmission power of all vehicles in the vehicle controls the channel load within a certain range to avoid channel congestion. Through experiments, the results show that the algorithm can effectively control the channel load and avoid channel congestion, which enhances the vehicle network wireless beacon transmission stability.

Wu et al. (2020) proposed a power allocation scheme for vehicle-mounted cooperative communication based on the signal-to-noise ratio threshold. First establish a general traffic flow channel model, and then determine the appropriate cooperative node according to the signal-to-noise ratio capture effect model. Finally, the expressions of source node power and cooperative node power allocation are derived from the system's outage probability. Experiments show that compared with the equal power distribution scheme, the performance of this scheme has been significantly improved. However, the performance of the method in the article is not known when the vehicle density is high.

Yu et al. (2019) designed an IOV beacon message transmission power control algorithm based on channel load prediction. It evaluates the channel load at the current time through the channel busy time ratio (CBR), and predicts the load of the channel at the next time according to the differential autoregressive integrated moving average model (ARIMA). The preset thresholds are compared to adaptively adjust the beacon transmission power at the next moment to avoid channel congestion. Simulation experiments show that the algorithm can effectively reduce communication transmission delay, avoid channel congestion, and ensure reliable data forwarding.

Zuo et al. (2017) proposed a distributed weighted fair power control distributed-weighted fair power control (D-WFPC) algorithm. It is to control the local channel load below the threshold, and through a distributed algorithm, each vehicle dynamically adjusts the transmit power according to the beacon messages of neighboring vehicles in the surrounding environment. Through simulation experiments, compared with the fixed transmission power scheme, as the traffic density increases, the D-WFPC algorithm can effectively reduce the delay and packet loss rate, ensuring low latency and high reliable transmission of messages in the internet of vehicles. But the power control method of the article needs to be improved.

Based on the above analysis, the starting point of VANET research is the application of vehicle safety. This paper starts with the transmission power of vehicle beacon message, and adjusts the transmission power of beacon message according to the location prediction error of vehicle, so as to effectively reduce the network burden, reduce the possibility of channel congestion, improve the transmission efficiency of safety information, and improve the driving safety of vehicle.

3 Adaptive beacon transmission power transmission control algorithm based on prediction error

3.1 Error calculation

In the internet of vehicles environment, each vehicle is equipped with a corresponding positioning system or device. In addition to the errors caused by the system itself, data transmission delay and packet loss are also the main factors that affect the mutual positioning of vehicles. Common methods to reduce errors include increasing the transmission power or transmission frequency between vehicles, but if all vehicles in the range send beacon messages with a large power or a small cycle, it will inevitably cause channel congestion, serious it can even cause broadcast storms.

In order to solve this problem, this paper proposes an adaptive vehicle beacon message transmission power algorithm based on prediction error. Its core idea is: the greater the error between the vehicles, the more uncontrollable between the two vehicles, you need to increase the transmission power of beacon messages, so that the vehicles can accurately grasp each other's position and reduce safety accidents; For small errors between the two vehicles, we will appropriately reduce the power of sending beacon messages, in order to reduce the burden on the channel as much as possible.

According to the above explanation, we understand how the current first step is to know the position error between the two vehicles. The current commonly used method is the linear prediction algorithm. This method is more suitable for highway scenes or straight roads. However, there will be many road junctions in urban scenes. Using the linear prediction algorithm will have a large error when the vehicle turns. Let's take the ordinary 90° turn as an example (Li et al. 2017a, b). Figure 2 shows a trajectory diagram of a common vehicle turning. The drawing interval is 1 s for a total of 10 s. Each point represents the position of the vehicle at that moment.

It can be seen from Fig. 2 that after the fourth second, the vehicle has a continuous speed direction change, and the traditional linear prediction algorithm will judge that the vehicle is still moving linearly. At this time, the position prediction error between the vehicles will be very large. It will become uncontrollable between cars, easily causing safety accidents.

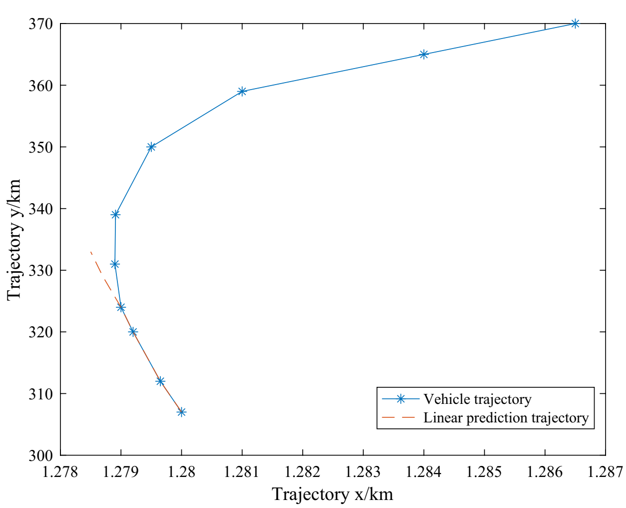


Fig. 2 Schematic diagram of the turning trajectory of the vehicle within 10 s

In this regard, we have considered that the turning of the vehicle is a continuous process, and the speed of the vehicle will be lower when turning than when driving in a straight line. If we can predict the vehicle to turn in advance, the error can be reduced. It can be understood from Fig. 2 that the vehicle continuously changes in the speed direction when turning. Therefore, as long as we find that the speed of the vehicle changes continuously, we can predict that the vehicle will be turning. Based on this idea, we improved the traditional linear prediction method and proposed a linear combination model.

The detailed derivation process of the algorithm is described in our previous article (Zhang et al. 2020), so we will not describe the derivation process in detail in this article, but only discuss the prediction error after using the linear combination model:

$$\varepsilon = L_T - L_P \tag{1}$$

where ε is the prediction error, L_T is the true distance, and L_P is the predicted distance.

3.2 Adaptive transmission power control algorithm

Since the turning of the vehicle is predicted in advance, we can further reduce the prediction error between the vehicles. However, it is impossible to achieve complete zero error. Therefore, we must give vehicles with large errors to send beacon messages with higher power so that the surrounding vehicles can more accurately grasp important status information such as their location. Due to the inconsistent reaction time of different drivers in the face of dangerous situations, and the braking effect of different vehicle parts. We have considered a relatively universal situation. The braking distance of a general vehicle on a smooth asphalt road at 30 km/h is about 6 m. For safety, we set the safe braking distance to 10 m in this article. Give the driver sufficient reaction time in case of danger.

After passing through the linear combination model, the prediction error between vehicles has been greatly improved, and the current error basically comes from the transmission control level. In the CSMA/CA transmission mechanism, when multiple nodes send data together, channel contention and backoff will occur (Chen et al. 2019; Jiang et al. 2020a, b, c). When there are too many nodes, some nodes will continue to delay or even lose packets. Therefore, we give different transmission power to the vehicle based on its prediction error. If the prediction error is greater than 10 m, we will appropriately increase the transmission power of its beacon message; and if the prediction error is less than 10 m, we will appropriately reduce the transmission power of its beacon message.

The adaptive beacon transmission power algorithm based on prediction error is as follows:

$$P_v = \left[P_\omega {}^* e^{\frac{\varepsilon}{10}-1} \right] + \theta. \quad (2)$$

Among them, P_v is the adaptive beacon transmission power, P_ω is the fixed beacon transmission power, and θ is the balance parameter. In this paper, θ = 0.01.

4 Pretreatment before experiment

4.1 Coping with signal weakness

In the urban road environment, vehicle nodes move rapidly, and the topology changes frequently. At the same time, external environments such as roads, trees, and buildings cause wireless signals to generate physical phenomena such as reflection, diffraction, diffraction, and scattering during transmission, which seriously affects the signal. Successful reception, and as the communication distance increases, the path attenuation of wireless signals becomes more and more serious (Li 2016). The signal attenuation during wireless communication is shown in Fig. 3:

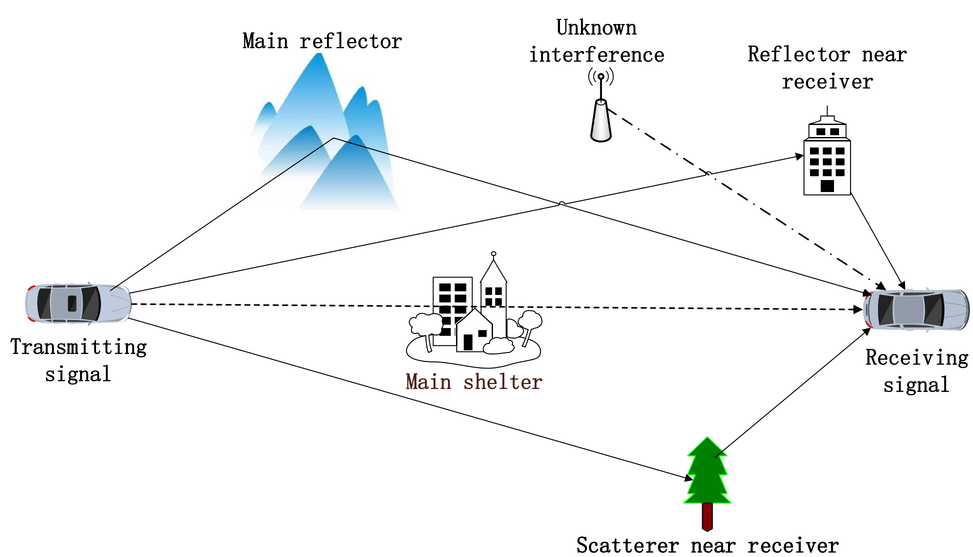
It can be seen from Fig. 3 that as the distance between vehicles increases, the signals between them will become weaker and weaker, which will greatly hinder the exchange of information between vehicles. To this end, we have performed a simple pre-processing, that is, selectively ignoring the information of long-distance vehicles. In a normal driving environment, if the distance between vehicles is too far, it can be regarded as having no effect on each other, and there is no possibility of an accident. Except for the warning message, it can inform the existence of long-distance vehicle accidents and allow vehicles to avoid accidents as much as possible to avoid traffic jams or serial rear-end collisions. Since the experimental communication range of this article is 1000 m, we ignore the information that the distance between the two vehicles exceeds 300 m, that is, if the vehicle receives a message that the vehicle is 300 m in the driving process, it will automatically ignore the message and will not Perform forwarding so as not to occupy channel resources.

4.2 Respond to channel contention

Within the communication range, each vehicle acts as a sending node and sends messages to multiple vehicles (receiving nodes) around it. However, if multiple nodes simultaneously send messages, there will be channel contention. If a sending node that does not successfully compete for a channel does not successfully transmit within the backoff time slot, it will clear it from the queue (Sun 2016). At the same time, since the receiving node can successfully receive and parse the radio waves successfully transmitted by the nodes in the communication range, the node can receive the Beacon message sent by the nodes in the communication range. There are two main conflicting ways of beacon messages in the Internet of Vehicles: merge conflict and access conflict, as shown in Fig. 4.

The key mechanism of shared channel access in 802.11p is binary exponential back-off (BEB). In order to minimize the probability of simultaneous beacon transmission, vehicles wishing to transmit will first need to select the backoff slot time from the current contention window (Torrent-Moreno et al. 2006). But unlike unicast transmission, BEB is not suitable for periodic beacons. This means that periodic beacons need to be transmitted with the smallest contention window size. If the beacon cannot be transmitted after the specified backoff expires, it will be cleared from the queue.

Fig. 3 Signal attenuation during vehicle communication



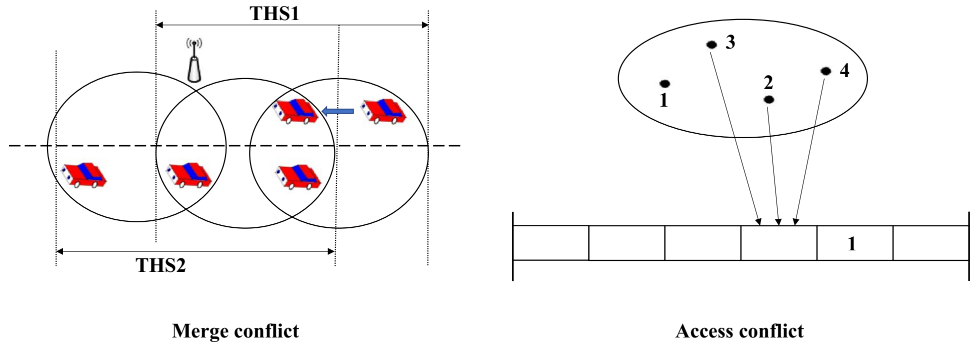


Fig. 4 The merge conflict and access conflict

Therefore, by introducing a minimum latency before transmission, a smaller contention window size is used to reduce latency. However, if the contention window is small, the contention for the channel will be very fierce when the vehicles are dense. Therefore, if the congestion control beacon strategy is not used, synchronization conflicts will increase and the perception will decrease. It can be seen that the design of 802.11p does not meet the perception requirements of vehicle networks in high-density networks.

The adaptive power control proposed in this paper can overcome this difficulty, and it will determine the power of the vehicle to send messages according to the error of the vehicle. Vehicles with larger errors are less controlled, so their transmission power is increased, so that as the frequency of beacon message transmission increases, the probability that the beacon successfully contends for the channel will increase, allowing the receiving node vehicles to better grasp each other's information.

4.3 Set max beaconing load

Messages related to vehicle active safety applications in IoV are divided into periodic Beacons messages and warning messages triggered by emergency events. From a security perspective, periodic information can be viewed as preventive information. They transmit information about the status of the sending vehicle, ie, position, direction, speed, etc., and may also gather data about the status of their neighbors. The content of the message is beneficial to all vehicles around. The main goal of the beacon is to increase the driver's awareness of the surrounding environment. On the contrary, the warning message is the result of the detection of danger, as shown in Fig. 5 such as emergency braking from a car, emergency vehicles traveling at high speed, etc. Therefore, the information they transmit is also the most important for relatively distant nodes, and they should propagate as fast as possible along the road. The purpose of event-driven information is to enable the driver to take appropriate countermeasures in an emergency: if the driver becomes aware of the danger a few seconds (or even seconds) before actually seeing the danger, then several accidents can be avoided.

However, the adaptive power algorithm in this paper does not take warning messages into consideration. Therefore, if the transmission power of vehicle beacon messages exceeds a certain limit, the channel may be occupied by beacon messages. In major traffic accidents, warning messages cannot be sent to surrounding vehicles, and the consequences will be unimaginable. Therefore, we must add an extreme value of load to our channel, namely max beaconing load (MBL). researchers such as Fallah et al. (2010a, b) have found through experiments that when the channel occupancy rate reaches 70%, the maximum throughput can be achieved to optimize the network performance. Therefore, we also limit the channel load to 70% of the channel capacity to achieve optimal network performance.

5 Experimental simulation and analysis

5.1 Experimental parameter settings

In order to make the experimental simulation scene as close as possible to the actual urban road environment, we used simulation of urban mobility (SUMO) (Behrisch et al. 2011) traffic simulation software to build a two-way two-lane road model of the city, and the map is from the publicly available Nanchang area in China (Figs. 6, 7). In this paper, the road range is 1000 m $\times$ 1000 m urban roads, the number of vehicles varies from 0–100, the driving speed of vehicles is 15-20 m/s, they are randomly distributed in the road, and the traffic lights will be operated accordingly, After the end of the experiment time of 100 s, drive out of the map.

After configuring the relevant parameters in SUMO, we need to import the results into Network Simulator 2 (NS-2) (Zhang 2014), and then configure the relevant network simulation parameters in NS-2. The packet type uses the constant bit rate (CBR) data stream, the communication packet size is 800 bits, the data transmission rate is 12 Mbps, then the MBL of this article is set to 8.4 Mbps, the transmission protocol is UDP, the routing protocol is destination sequenced distance vector (DSDV). At the MAC layer, choose the IEEE 802.11p protocol that is mainly used for in-vehicle electronic

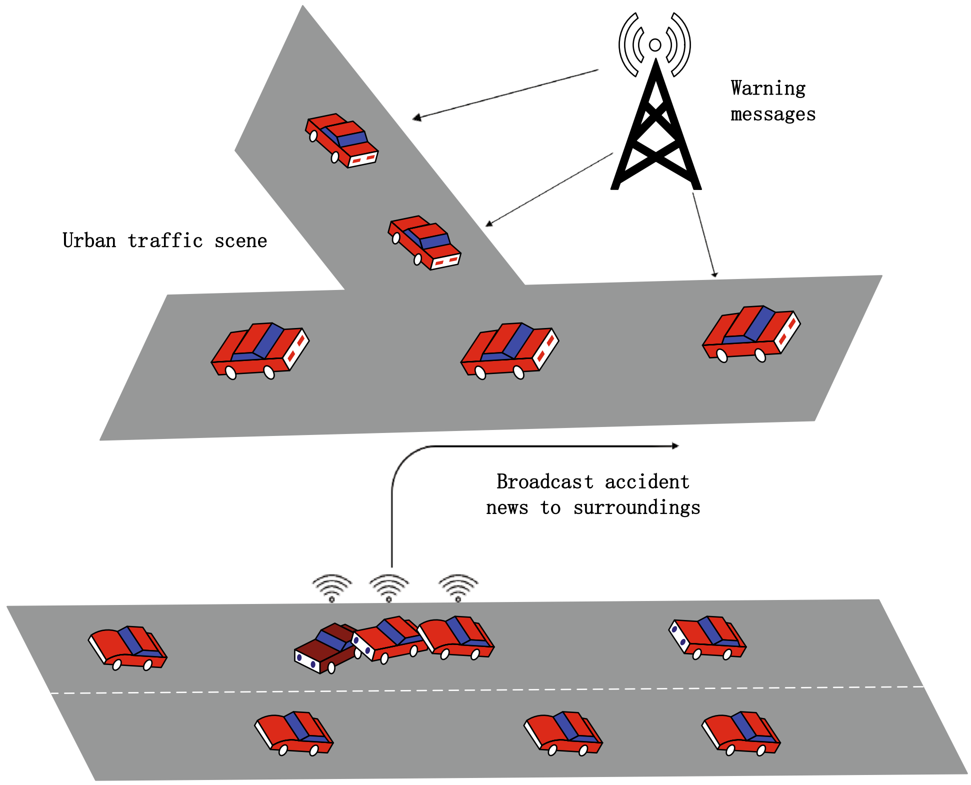


Fig. 5 The proliferation of warning messages in urban scene

communications. The beacon message generation period is set to 100 ms; the power control period is set to 1 s, because the relative position change between vehicles within 1 s is small in the conventional case. According to the literature (Cheng et al. 2007), the fixed transmission power is set to 18dBm, which can ensure that all vehicles communicate normally within the communication range.

In order to understand the influence of different wireless propagation models on the algorithm in this paper, we compare three representative channel attenuation models: the deterministic two-ray ground (TRG) model, and the probabilistic log-normal shadowing (LNS) and Nakagami (Nak) models. For the configuration of the relevant parameters of the three models, we refer to the article (Torrent-Moreno et al. 2006), For the TRG model, as implemented in ns-2.28, provides a diskrange model; for the log-normal shadowing model, path loss exponent = 2 and a shadowing deviation = 6 dB; for the Nakagami model, fading intensity m = 3 for distances up to 50 m, m = 1.5 for distances between 50 and 150 m, and m = 1 for distances larger than 150 m.

The experiment is divided into three groups of control experiments, which are the comparison between the fixed transmit power and the adaptive power of this paper under different attenuation models.

The specific experimental parameters are shown in Table 1:

Because the experimental results may not be accurate enough, we use the LNS fading model to analyze the error of the experiment with 15 packet delivery rate when 100 vehicles send beacon messages at a fixed power. The error bars are shown in Fig. 8. The blue column is the average of each set of experiments, and the red line is the standard deviation of each set of experiments. The formula for calculating the mean and standard deviation (Wang and He 2018) is as formula (3) and Formula (4) shown:

$$\bar{x} = \frac{\sum_{i=1}^{m} x_i}{m}, \tag{3}$$

$$SD(x) = \sqrt{\frac{1}{m}\sum_{i=1}^{m}(x^i - \bar{x})^2}, \tag{4}$$

where m = 15.

As can be seen from Fig. 8, the experimental error range is not large, the error is within an acceptable range. After analysis, we selected the data with the smallest experimental error in each group.

5.2 Simulation experiment results analysis

The simulation in this paper is mainly based on the analysis of different vehicle numbers and different channel attenuation models. The number of vehicles varies from 0 to 100. The channel models are TRG, LNS and Nak models. The simulated network performance parameters mainly include: (1) channel busy time (CBT), which is the

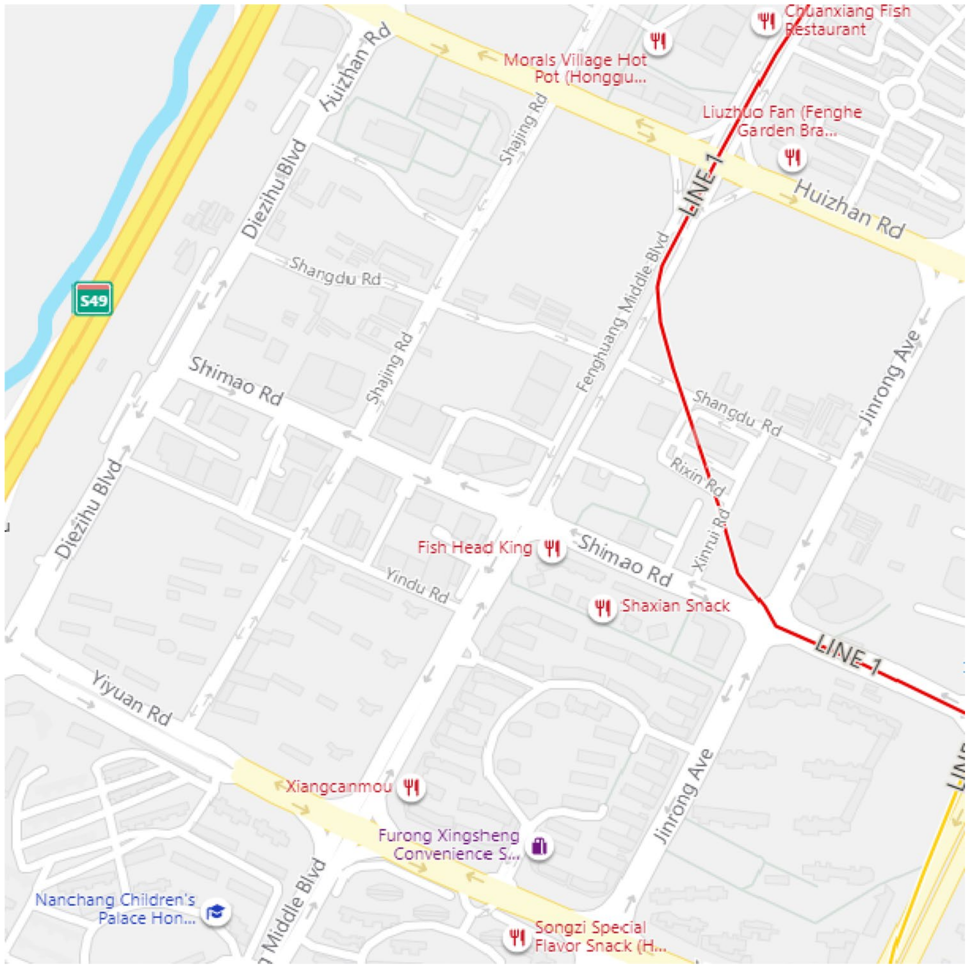


Fig. 6 Nanchang partial map data

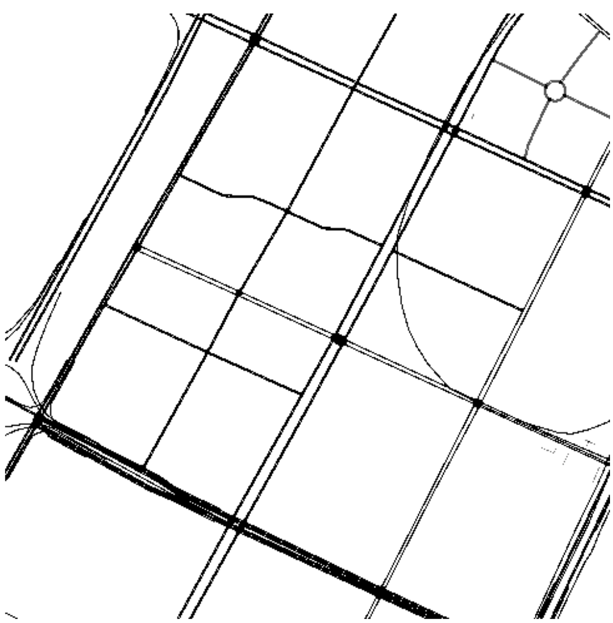


Fig. 7 Nanchang local map topology

Table 1 Simulation parameter settings

Parameter	Value
Number of nodes	0–100
Vehicle speed	15–20 m/s
Scene size (m^2)	1000 × 1000
Transmission range (m)	1000
Data rate	12Mbps
MBL	8.4 Mbps
Fixed transmit power	18 dBm
Packet size	800 bits
Mac layer protocol	IEEE 802.11p
Transport layer protocol	UDP
Routing protocol	DSDV
Antenna gain	4 dB
Antenna height	1.5 m
Type of data	CBR

percentage of channel busy and idle time per unit time; (2) packet delivery rate, which is the number and source of status information packets received per unit time The ratio of the total number of packets sent by the node.

Figures 9, 10 and 11 depicts the average CBT of all vehicle nodes in the network under different wireless propagation models. From these three figures, we can clearly see that aside from different channel fading models, the adaptive power in this paper can significantly reduce CBT compared

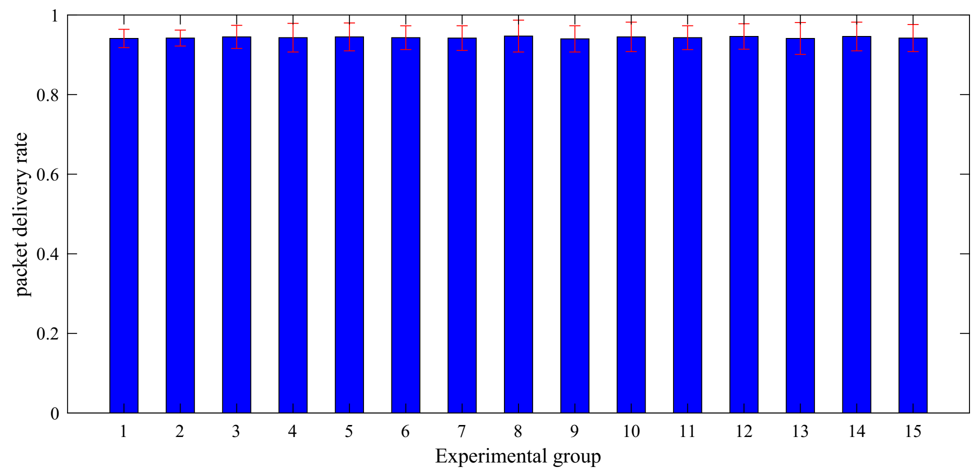


Fig. 8 Error bar graph for 15 groups of experiments

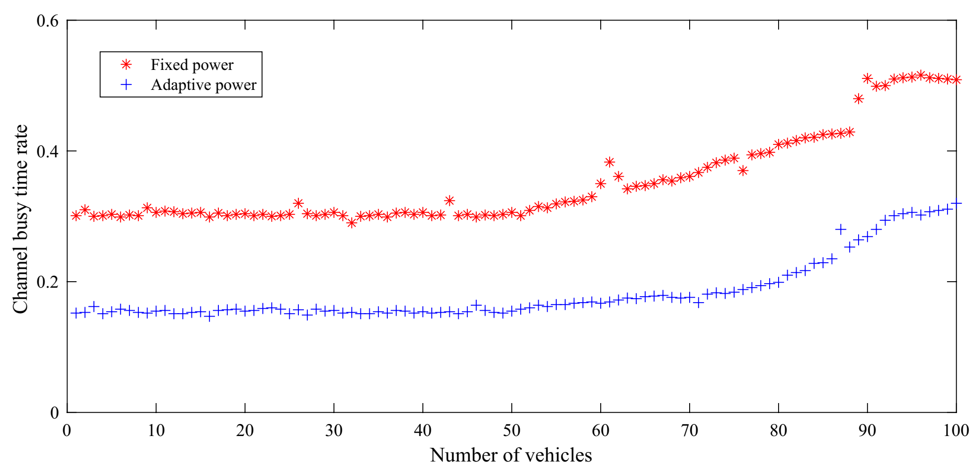


Fig. 9 Channel busy time of each vehicle in the urban scenario with two-ray ground model

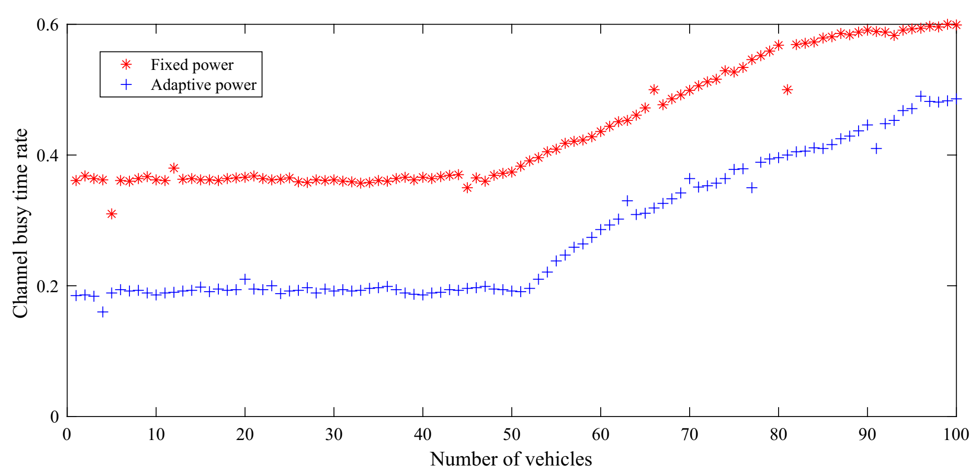


Fig. 10 Channel busy time of each vehicle in the urban scenario with log-normal shadowing model

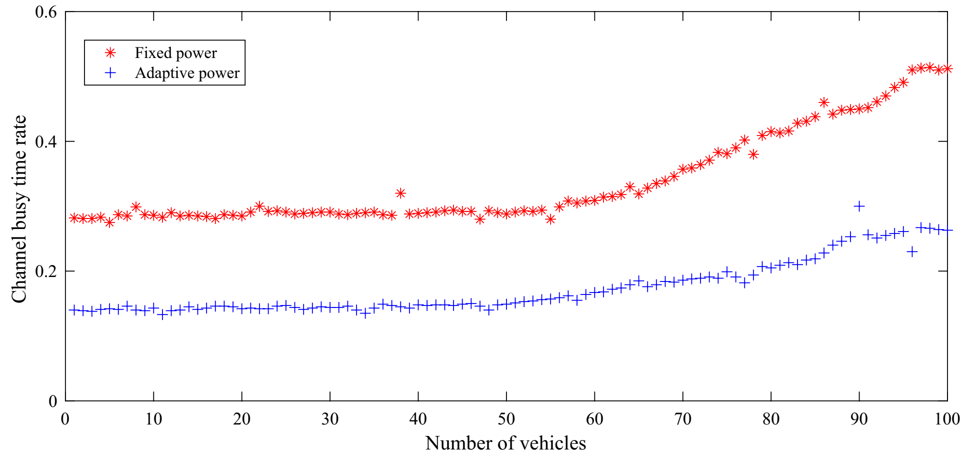


Fig. 11 Channel busy time of each vehicle in the urban scenario with Nakagami model

to fixed power, in the two-ray ground model, CBT is reduced by approximately 16.86%; in the log-normal shadowing model, it is approximately 16.18%; and in the Nakagami model, it is reduced by approximately 16.47%. Taking the TGR model as an example, the CBT of some vehicle nodes has decreased by 0.23, which is about 53%. The reduction in average CBT provides more bandwidth resources for vehicle information exchange, which makes more channel space available for warning messages and improves the rate at which warning messages are received.

In addition, we see that the CBT value with the highest absolute value is experienced in the LNS model. This is because the experimental environment in this article is in an urban scene with many tall buildings. The external environment causes physical phenomena such as reflection, diffraction, diffraction and scattering during the transmission of beacon messages, and the signal decays faster. Since many vehicles cannot receive the message, the target vehicle needs to continuously send beacon messages, thereby causing problems such as a busy channel.

Figures 12, 13 and 14 depicts the relationship between fixed transmit power and adaptive power control packet delivery rate for different vehicle numbers and different signal attenuation models. It can be seen from the figure that with the increase of vehicle nodes, the delivery rate of data packets has decreased, but the delivery rate of adaptive power is significantly higher than the fixed transmission power, this is because the adaptive power of this article is different The beacon messages of the vehicles with different transmission powers enhance the transmission power of the beacon messages of the uncontrollable vehicles and increase the probability of their contention for the channel. Among them, in the two-ray ground model, the packet delivery rate increased by about 1.5%; in the log-normal shadowing model, it was about 4.03%; and in the Nakagami model, it increased by about 7.99%.

For different channel models, unlike the TRG model's relatively stable delivery rate, the packet delivery rate of the LNS and Nak models begins to decrease with the increase of vehicle nodes. This is because when using more realistic propagation models (such as LNS and Nak), the reception probability is lower than the deterministic propagation (such as TRG), which is closer to the real Internet of Vehicles driving environment.

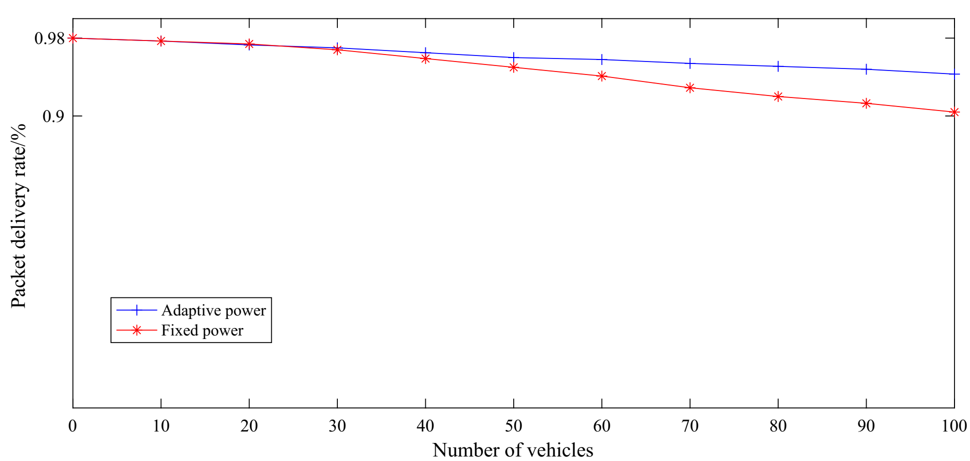


Fig. 12 Packet delivery rate with two-ray ground model

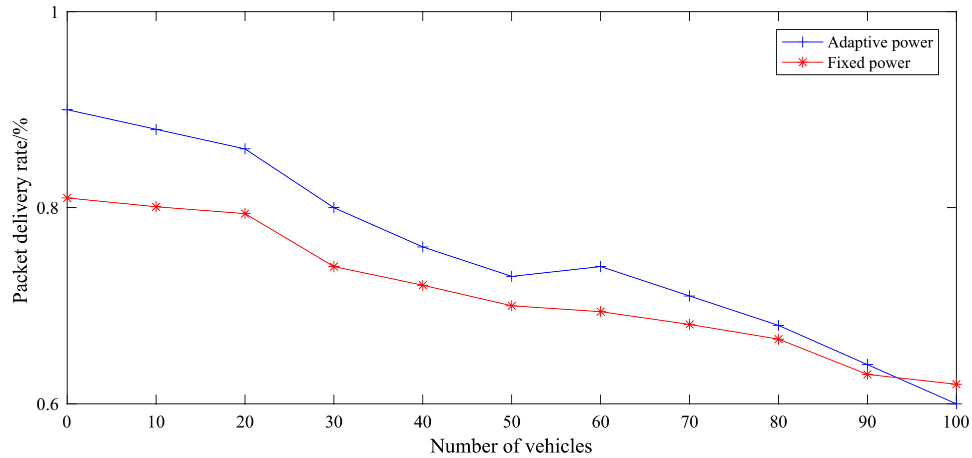


Fig. 13 Packet delivery rate with log-normal Shadowing model

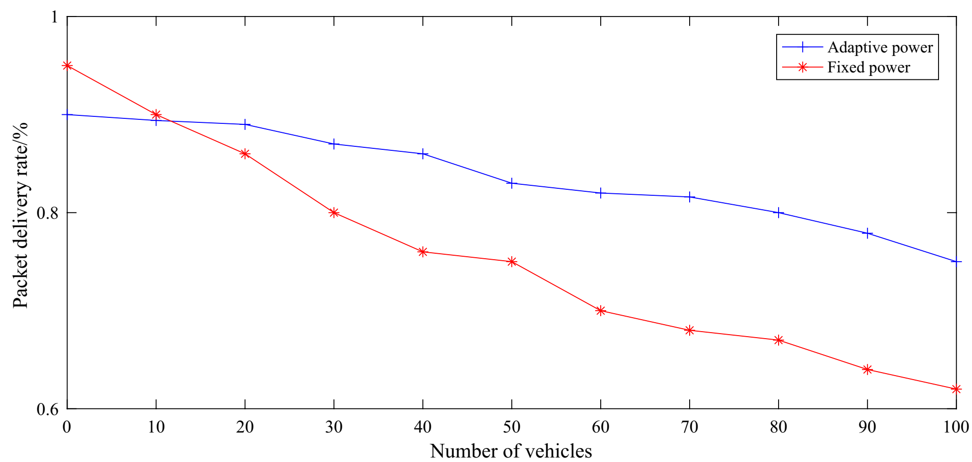


Fig. 14 Packet delivery rate with Nakagami model

Finally, because our algorithm automatically ignores related messages beyond 300 m, beacon messages are affected by distance and we will not discuss them in this article.

6 Conclusion

In vehicle safety applications, due to limited channel resources, the safety warning information cannot accept continuous delay and packet loss, so this paper proposes an adaptive beacon transmit power algorithm based on vehicle position prediction error. First of all, we improve the traditional linear prediction algorithm, and elaborate a linear combination model to reduce the vehicle's turning error. Subsequently, our adaptive power algorithm was proposed to increase the transmission power of beacon messages of dangerous vehicles with large prediction errors, and vice versa to reduce the transmission power of vehicles with small errors. We then formulated relevant solutions to signal fading and channel contention by analyzing the relevant factors that may affect the results in the experiment. Finally, we conducted experiments under three different channel models to compare the fixed beacon message transmission power with the adaptive beacon message transmission power in this paper. The experimental results show that, compared with the fixed transmit power, the proposed adaptive power reduces the CBT by about 16% and improves the packet transmission rate by about 4.5%, ensuring the effective transmission of security information.

However, the number of vehicle nodes in this paper is not sufficient, and the influence of more vehicle nodes on different channel models is unknown. Therefore, the next step in this article is to increase the number of vehicles in the experiment and explore the effect of distance on beacon messages.

Acknowledgements We are grateful for Juan Wang, Guanxiang Yin from East China Jiaotong University for their constructive suggestions on the experiments. We are also grateful for the supports from National Natural Science Foundation of China, Natural Science Foundation of Jiangxi Province, Transportation Department of Jiangxi Province, Education Department of Jiangxi Province.

Author contributions All authors have contributed to the concept and design of the study. The project was designed by YZ and JW. The experiment was designed and executed by MW, FD, JW, GY and TC. YZ and MW wrote this manuscript with the help of all other authors. All authors have read and approved the final version of the manuscript.

Funding This study was funded by National Natural Science Foundation of China (Grant numbers: 11862006, 61862025), Natural Science Foundation of Jiangxi Province (Grant numbers: 2018ACB21032, 20181BAB211016), Research Project of Transportation Department of Jiangxi Province (Grant number: 2018X0016), Education Department of Jiangxi Province (Grant numbers: GJJ170381, GJJ170383) and China Scholarship Council (Grant number: 201808360320).

Compliance with ethical standards

Conflict of interest The authors declare that they have no conflict of interest.

Availability of data and material All data and material generated or analyzed during this study are included in this published article.

Code availability All code generated or used during the study are available from the corresponding author by request.

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