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Risk-Based Transmission Control for Mitigating Network Congestion in Vehicle-to-Everything Communications

LAN-HUONG NGUYEN^{(1,2}, VAN-LINH NGUYEN^{(1,2}, (Member, IEEE), AND JIAN-JHIH KUO^{(1),3}, (Member, IEEE) ¹Department of Computer Science and Information Engineering, National Chung Cheng University, Minhsiung, Chiayi 621301, Taiwan

¹Department of Computer Science and Information Engineering, National Chung Cheng University, Minhsiung, Chiayi 621301, Taiwan ²Department of Information Technology, University of Information and Communication Technology, Thai Nguyen 664074, Vietnam ³Advanced Institute of Manufacturing With High-Tech Innovations, National Chung Cheng University, Minhsiung, Chiayi 621301, Taiwan

Corresponding author: Jian-Jhih Kuo (lajacky@cs.ccu.edu.tw)

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ABSTRACT Vehicle-to-Everything (V2X) communication technologies and High-definition (HD) maps are essential to improve the safety of vehicles in areas with limited visibility. V2X-enabled vehicles use periodic beacon messages to update each other on their moving state (position, velocity, heading). However, due to the limited resources of V2X wireless channels, the explosion of data pouring into the network (e.g., from a crowded group of connected vehicles) can exhaust bandwidth and cause severe network congestion. Consequently, the rapid drop of sharing messages can threaten the safety of connected vehicles due to lost tracking. In this work, we present an efficient risk-based transmission control model, namely RTC+, to automatically control the time interval for broadcasting beacon messages of the connected vehicles in V2X networks. RTC+ works at the application layer to minimize interference with algorithms in the low layers (e.g., MAC). Two new algorithms are proposed in RTC+. The first one is RiskSCAN, a robust risk management algorithm to check and determine whether a vehicle suffers the risk of a potential collision with its neighbors. The second is RateCONTR, an adaptive broadcasting rate control to adjust the time interval of sharing messages, particularly when bandwidth is limited to serve all channel requests. The evaluation results show that RTC+ can significantly increase 25% of packet delivery rate while mitigating the collision threats compared with the default time interval in current vehicular network settings.

INDEX TERMS Vehicular networks, V2X network congestion avoidance, transmission control.

I. INTRODUCTION

Vehicle-to-Everything (V2X) technology is vital for autonomous vehicles and Intelligent Transportation Systems (ITS), particularly in areas with limited visibility. For example, when an autonomous vehicle approaches an unsignalized intersection, its cameras and radars may not be able to detect the vehicles approaching from different directions because of the obstacles of the buildings. Several fatal accidents in high-end cars [1] also reveal the flaws of built-in sensors such as cameras and LIDAR/radar in working under harsh weather conditions and obscured vision [2]–[4]. To this end, V2X was invented to assist vehicles in driving under such

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cases. Through V2X, a vehicle can share its sensing data with the surrounding vehicles. By using *data sharing*, the receiver vehicles can have a better view of the surrounding traffic and thus reduce potential risks of sudden accidents [5].

However, network congestion is an open challenge in V2X networks [6], [7]. First, V2X spectrum and bandwidth are limited, even with 5G V2X [8], [9]. To reflect the latest updates of the vehicle movement, User Equipment (UE) in V2X-enabled vehicles must broadcast at least 30 Cooperative Awareness Message (CAM) per second [10] (per vehicle) or even more. In the urban driving condition, each CAM can surpass 6000 bytes [10] or even 1GB per second if video streaming and LIDAR raw data are shared [4]. With a dozen vehicles sharing simultaneously, the network bandwidth can quickly become exhausted. The demand for extensively simultaneous

applications (e.g., infotainment) can worsen *network congestion* [11]. Therefore, efficient congestion control in different layers for vehicular networks has been the target of many studies for years [12]–[16].

There are many approaches to resolve network congestion in vehicular networks. The Society of Automotive Engineers (SAE) and the European Telecommunications Standards Institute (ETSI) specified Decentralized Congestion Control (DCC) mechanisms for Dedicated short-range communications (DSRC) IEEE 802.11p [17]-[20]. DCC uses periodic channel probes and calculates Channel Busy Ratio (CBR) rate during a measuring interval 1s to control a vehicle's channel access. The message transmission rate can be tuned based on sensing channel busy percentage [21], [22]. In academic research, Sewalkar et al. presented a multi-channel congestion control algorithm by clustering the user requests based on their locations and directions [13]. As the authors suggest, using separate channels for exchanging cluster and safety messages can reduce the control information overhead. In another study, Choudhury et al. [23] present a self-risk assessment for improving the safety of 802.11p based V2V Networks. However, the system does not consider a mutual check to verify the accuracy of self-estimation in each vehicle. Note that the accuracy of self-assessment can be overestimated and accidentally risk the safety of the surrounding vehicles. For Cellular-V2X (C-V2X) networks, 3rd Generation Partnership Project (3GPP) defined a general framework for access-layer congestion control for LTE-V2X and 5G New Radio V2X [12], [24]. The control uses sensing-based semi-persistent scheduling (SB-SPS) mechanism to manage the congestion through scheduling resource reservation interval (RRI) [12]. The resource reservation interval is set to one of the allowed values {20, 50, 100, 200, ..., 1000 ms}. The common points of the proposed congestion controls are based on sensing the channel busy, packet dropping rate or channel occupancy [25], [26]. Historically, this approach works well in most cases for both DSRC and C-V2X. However, the channel-based congestion control approach lacks "intelligence" of knowing which vehicles need the resources at most to prioritize the data transmission that is crucial in emergency cases. For example, a large number of vehicles moving on the highway demand as much as possible connection resources for the sake of safety and their personal infotainment. And then satisfying such all requests "mechanically" can result in channel overload and network congestion. As a result, probably, no vehicle gets adequate resources or time slots they requested. Worse, the transmission interruption can lead to potential on-road safety hazards such as shockwave traffic jams or tailgating crashes.

Unlike prior studies, this paper makes the first attempt to mitigate network congestion by evaluating vehicles' risk and then controlling their broadcasting rate accordingly. This method addresses the root causes of the network congestion by lengthening the time interval for broadcasting beacon messages, i.e., reducing the broadcasting rate at the application where generating data. Generally, there are two challenges to pursue this approach. The first one is to determine which vehicle will reduce broadcasting rate. Generally, all vehicles must broadcast beacon messages to the neighbors at a certain period, e.g., per 100ms [10], to maintain their up-todate moving states. However, if using a fixed broadcasting rate, a large amount of data sharing from multiple vehicles can accidentally cause congestion and degrade the goal of the sharing. With the limited bandwidth, there is no way to satisfy the channel usages of all vehicles without potential congestion. Reducing the broadcasting rate at several vehicles can significantly save valuable radio resources and bandwidth in V2X networks. Unfortunately, it is a challenge to know which vehicles are qualified for decreasing the broadcasting rate. The second challenge is to guarantee the safety of the vehicles if performing a series of broadcasting rate reductions. Since safety requirements must be the priority, the data sharing must be adequate for fusing in the receiver vehicles; otherwise, improper rate control can cause the receivers to get outdated information and thus fail to sense the approaching dangerous obstacles/vehicles. In summary, there is a tradeoff between reducing broadcasting rate while still satisfying safety requirement. Balancing the trade-off becomes a significant issue.

To address the challenges, this work presents an efficient Risk-based Transmission Control (RTC+), to mitigate the network congestion and maintain reliability in V2X communications. RTC+ includes two algorithms. The first one is a Risk-Scanning (RiskSCAN) algorithm. The goal of RiskSCAN is to check and determine whether a vehicle suffers the risk of potential collision with its neighbors by monitoring the difference between the actual value and estimated value of several measurement factors such as Time-to-Collision. Given the results of the risk assessment from RiskSCAN, a novel algorithm, namely Rate-Control (RateCONTR), will suggest a proper rate for broadcasting V2X messages. Through the modeling, we show an important lesson that increasing broadcasting rate to reflect the latest updates of the vehicle movement does not always improve the overall safety of the driving. By contrast, the increase of broadcasting data into V2X networks can cause potential network congestion and then risk the safety of the vehicles due to lost tracking. Also, our risk-based transmission control model can maintain the vehicles' safety while not sacrificing valuable bandwidth for transmitting redundant data. Finally, we found that a mutual check to verify the accuracy of the risk assessment periodically is also critical to prevent potential over-self-confidence evaluation in the risk-based rate control approach. For example, one vehicle may think the other vehicles are not risky (because of wrong tracking error estimations) and reduce the broadcasting rate. As a result, the risks increase on the ground, but the vehicles may not be aware. Due to working on the application layer, our

method can assist in enhancing the performance of the lowlayer technologies, e.g., [27], [28].

Our main contributions are summarized as follows.

- Inspired by the urgency of improving the safety of V2X, we propose RTC+, an efficient risk-based transmission control scheme at the application layer, to control the time interval of broadcasting V2X messages. RTC+ can significantly mitigate potential network congestion in high traffic density. By measuring the risk of vehicles, the scheme can prioritize allocating the bandwidth for the vehicles' needs at most, thus improving the overall safety of the vehicles relying on V2X sharing data.
- Our scheme can enhance channel-based congestion control – which is essential in vehicular communications. The evaluation results demonstrate the significant effects of the method in reducing the potential congestion for on-road safety applications.
- The risk management in our control can enhance the accuracy of the self-rate control and prevent the self-confidence of risk estimations. To the best of our knowledge, the verification-aided risk assessment scheme is the first attempt of its kind.

The remainder of this paper is organized as follows. Section II presents our assumption and problem formulation. The details of our proposed risk management and rate control scheme are presented in Section III. The evaluation results of the proposal are shown in Section IV. Finally, the conclusion and future work are summarized in Section V.

II. SYSTEM MODEL AND PROBLEM FORMULATION

After the recent US Federal Communications Commission (FCC) decision [29], vehicular communications are likely the lane of the C-V2X technology only. However, by working on the application layer, our solution can work with both DSRC and C-V2X standards. In fact, our solution aims to reduce application data volume by adjusting the data rate that indirectly reduces pressure for the transmission control mechanism in the MAC layer (e.g., CSMA/CA in DSRC or SB-SPS in C-V2X) instead of changing the MAC algorithm. Given the difficulty of modifying a well-established standard, our application-based approach is thus more practical to apply (easier to deploy). In this work, we assume all vehicles are equipped with at least a V2X-enabled On-board Unit (OBU). The vehicles communicate with each other through exchanging beacon messages, i.e., CAM [30]. The beacon messages can consist of (1) the vehicle dynamic information (e.g., position, velocity, and heading) and (2) meta information (e.g., identifier, vehicle type, size, and lane number). Generally, the vehicles must periodically broadcast these messages to maintain the updates of their moving state on the ground. Similar to [23], we assume there is a set of V2X-enabled vehicles (denoted by N) in a road segment with *m* lanes, as shown in Figure 1. Each vehicle $x \in N$, moves with a velocity v_x . The velocity v_x is limited by a threshold v_{max} (e.g., maximum allowed speed of the road).

Also, to update the HD map and the neighbor vehicles on its presence, vehicle *x* periodically broadcasts beacon messages at a time interval Δ_x . The time interval Δ_x can be any value in the range [Δ_{min} , Δ_{max}]. Depending on the velocity and the relative distance of the vehicles, the common value of Δ_{min} is often 20 milliseconds (ms) while Δ_{max} is 200 ms.

Communication delay (i.e., queuing delay, transmission delay, propagation delay) in wireless communications is nontrivial, particularly in a crowded transmission context. Following [26], we assume the delay denotes τ . For the vehicles relying on V2X data sharing, the delay τ will involve both the uplink (V2I) and downlink (I2V) communication delay. Intuitively, due to the existence of τ , there is a case that the vehicle *x*'s sent beacon messages are not able to arrive at the moving-nearby vehicles' OBU in time (i.e., within Δ_x). Network congestion can worsen the delivery and delay many vehicles to get up-to-date information about their neighbors. As a result, *the receiver vehicles may not be aware of the potential risks of nearby vehicles and make a wrong decision in the steering (e.g., lane changing or driving through)*.



FIGURE 1. The illustration of the importance of reducing redundant data transmission in V2X networks, in which the vehicle ① will assess the risk of the surrounding vehicles and adjust the broadcasting rate properly. Vehicle ③ and vehicle ④ do not likely give risk to the other vehicles due to the far distance, can reduce the broadcasting rate (i.e., longer Δ_X). By contrast, the truck ③ and the vehicle ① should maintain a more frequent update (shorter Δ_X).

Without loss of generality, we assume vehicle x tracks a neighbor vehicle y to evaluate its risk. Assume that vehicle y generates a beacon message at the time t^g (which can be extracted by vehicle x from the timestamp field of the beacon message) and t is the time of vehicle x received the message (i.e., $t^g < t$). The tracking error of vehicle x on vehicle y, namely e_{xy}^t , can be measured by:

$$e_{xy}^{t} = ||p_{y}^{t} - \hat{p}_{y}^{t}||, \qquad (1)$$

where p_y^t is true location of y at the time t and \hat{p}_y^t is y's estimated location at the time t by x. Note that \hat{p}_y^t can be predicted by vehicle x using extended Kalman Filter (EKF) [31] based on the position extracted from the last received beacon



FIGURE 2. The illustration of the self-tracking error of x and the tracking error on a vehicle y based on y's prior beacon message.

message of y (at the time t^g) and a motion model such as Constant Velocity (CV) or Constant Turn Rate and Acceleration (CTRA). However, knowing the exact value of p_y^t could be difficult for vehicle x. If vehicle y is in the range of x's radar or camera, p_y^t can be estimated quite accurately by using Doppler-based tracking [32], [33] or computer-visionaided tracking methods [34]. If vehicle x relies only on V2X communications (e.g., vehicle y is vehicle x's Non-Light-of-Sight (NLOS) areas), it is a challenge to know p_y^t exactly since vehicle y's beacon messages can arrive late due to potential communication delay. As a result, it is hard to estimate e_{xy}^t for vehicle x's risk assessment correctly.

To overcome the above issue, we employ the alternative way to estimate the tracking error of vehicle x, by *evaluating a self-tracking error*. The self-tracking error of vehicle x is exploited to estimate the tracking error on y. Let e_x denote the self-tracking error of vehicle x (i.e., the difference between vehicle x' ground truth location and its estimated location by the EKF-based tracking method). Then the *self-tracking error* of vehicle x can be estimated by Euclidean distance estimation:

$$e_x^t = ||p_x^t - \hat{p}_x^t||,$$
(2)

where p_x^t is the actual position of the vehicle x at the time t and \hat{p}_x^t is x's self-estimated location at the time t by using EKF [31] based on its previous location (at the time t^g). Typically, vehicle x can know its exact location (i.e., p_x^t) through Real-time kinematic positioning (RTK) systems [35]. To simulate the potential error of vehicle x's tracking method on vehicle y, we also use the EKF-based tracking method on x's location to estimate its location at the time t, i.e., \hat{p}_x^t . The self-tracking error e_x^t is critical since a large value of e_x^t means the failure of vehicle x to track itself correctly. If a vehicle cannot track itself well, the vehicle will unlikely be able to track the others. The large error on tracking presents a high risk of losing track of nearby moving vehicles. In this way, the self-tracking error e_x^t can be seen as an *indirect* metric to measure potential displacement on tracking the neighbor vehicles. The indirect measurement is important for self-risk assessment if vehicle x does not get y's beacon messages in time (within Δ_x) to have a ground truth location for comparison (i.e., p_v^t in Equation 1). Figure 2 illustrates two tracking error estimation methods: (1) self-tracking error estimation



FIGURE 3. The illustration of time-to-collision estimation and potential tracking error due to the delay of delivering the beacon message.

of x on its trajectory itself and (2) tracking error of x on y. Vehicle x prefers using the self-tracking error estimation to evaluate its risk with surrounding vehicles (detailed in the following paragraph) if the neighbor vehicles' beacon messages do not arrive within Δ_x , e.g., the network under congestion or heavy load.

For the sake of safety, vehicle x must maintain a certain distance with vehicle y, i.e., the safe gap distance. To measure the risk of vehicle x with vehicle y, similar to [36], we use a metric, Time-to-Collision (TTC). The metric TTC denotes the remaining time until a collision between two vehicles if the vehicles still keep their driving trajectories. Figure 3 illustrates two approaches to measure the safety among the vehicles: by time and by distance. The TTC of the pair of vehicles x, y at the time t can be calculated by:

$$TTC_{xy}^{t} = \begin{cases} \frac{||p_{x}^{t} - p_{y}^{t}||}{|v_{x}^{t} - v_{y}^{t}|}, & \text{if } v_{x}^{t} \neq v_{y}^{t};\\ \infty, & \text{otherwise,} \end{cases}$$
(3)

where v_x^t , v_y^t is the true velocity of vehicle x and vehicle y at the time t, respectively. Note that $v_x^t \neq v_y^t$; otherwise, the vehicles will likely maintain a stable distance as a string and there is no risk (i.e., TTC is infinite). Similarly, if both the vehicles stop, e.g., waiting for the red traffic light, the collision is unlikely, so the measurement should be only triggered when the vehicles start moving. Equation 3 indicates that the shorter the distance and the larger the difference in velocities between the vehicles are, the faster the collision can be. However, since we do not know the exact position and velocity of vehicle y (i.e., p_y^t , v_y^t), the expectation value of the TTC can be expressed by:

$$T\hat{T}C_{xy}^{t} = \frac{||p_{x}^{t} - \hat{p}_{y}^{t}||}{|v_{x}^{t} - \hat{v}_{y}^{t}|} = TTC_{xy}^{t} + \epsilon_{xy}^{TTC},$$
(4)

where \hat{v}_{y}^{t} , \hat{p}_{y}^{t} is the estimated velocity and location of vehicle y, respectively, and ϵ_{xy}^{TTC} is the time of tracking error.

Generally, ϵ_{xy}^{TTC} is estimated in two cases. If the camera/radar-based systems of the vehicles x, y are available for usage (e.g., in a Light-of-Sight (LOS) area), the error $\epsilon_{xy}^{TTC} = |TTC_{xy}^t - T\hat{T}C_{xy}^t| = \frac{||p_x^t - p_y^t||}{|v_x^t - v_y^t|} - \frac{||p_x^t - \hat{p}_y^t||}{|v_x^t - \hat{v}_y^t|},$ where $\hat{p}_{y}^{t}, \hat{v}_{y}^{t}$ are estimated via camera/radar-based tracking methods. By contrast, if V2X communications are available only (e.g., in NLOS area), given the potential delay of V2X beacon messages arrival, the simulated time error of tracking can be estimated by $\epsilon_{xy}^{TTC} = \frac{||p_x^t - \hat{p}_x^t||}{|v_x^t - \hat{v}_x^t|} = \frac{e_x^t}{|v_x^t - \hat{v}_x^t|}$, where \hat{v}_x^t is vehicle x's velocity that is self-estimated by using EKF [31] on its previous velocity (at the time t^g). Depicted in Figure 3 is a case of vehicle x assesses the TTC value to vehicle yin associate with potential errors of tracking. Due the delay of V2X communications, the true location of vehicle y can be different from the location in the beacon message which vehicle x received. The risk of potential collision between vehicle x and vehicle y will be high if the TTC TTC'_{xy} is smaller than a threshold TTC_{min} , where TTC_{min} is (1) defined as the time to pass through the safe gap distance or (2) can be measured by the time required for the vehicle to react t_{react} (steering the vehicle) to the possible collision and brake to stop t_{brake} , i.e., $TTC_{min} = t_{react} + t_{brake}$. In autonomous driving, with the help of computer control, treact is tiny and ignorable. The time for braking is $t_{brake} = \frac{v}{\dot{a}}$, where v is the current velocity of the vehicle and \dot{a} is the maximum deceleration. In practice, a vehicle moving at 20m/s (72km/h) does not often come to a stop in less than 5.0s if $\dot{a} = 4m/s$.

Based on the TTC estimation, the collision risk between two vehicles x, y at the time t is expressed by:

$$RIS_{xy}^{t} = \begin{cases} 1, & \text{if } T\hat{T}C_{xy}^{t} - \epsilon_{xy}^{TTC} - TTC_{min} < 0; \\ 0, & \text{otherwise.} \end{cases}$$
(5)

The collision risk $RIS_{xy}^t = 1$ means a risk case, i.e., the actual time to collision is shorter than the time needed to respond to a potential collision. Otherwise, $RIS_{xy}^t = 0$ indicates a non-risk case, i.e., the vehicles still have time to react and brake if necessary. In the non-risk case, the value of $T\hat{T}C_{xy}^t - \epsilon_{xy}^{TTC} - TTC_{min}$ can be used to measure the urgency of data update rate. In short, a higher positive value of $T\hat{T}C_{xy}^t - \epsilon_{xy}^{TTC} - TTC_{min}$ means two vehicles are far from each other and reducing broadcasting rate is acceptable. From Equation 4 and Equation 5, a key conclusion is that minimizing the tracking error ϵ_{xy}^{TTC} is critical to maintain an exact estimation of RIS_{xy}^t and then the safety of the vehicles. Without loss of generality, we assume $RIS_x^t = RIS_{xy}^t$ where y is the nearest front vehicle in the neighbor list of x.

To find the impact of the broadcasting rate on the safety of the vehicles, we define a new metric, Age of Information (AoI). AoI of vehicles (x, y) (denoted by ρ_{xy}) represents the time elapsed from the time t^g of vehicle y generating a message to the time of vehicle x receiving the sent message, i.e., $\rho_{xy} = t - t^g$. Intuitively, AoI is a metric to measure the



FIGURE 4. An illustration of two cases (low traffic, heavy traffic) of age of information in associate with beacon time interval Δ and resource reservation interval (RRI).

duration from the generation time of information at the sender to the receive time at the receiver. However, if the message is dropped, AoI is unknown. In this case, we use an observation interval T and then estimate the average AoI of the generatedreceived messages in T.

Figure 4 illustrates two possible cases of ρ . In the first case, vehicle y generates message 1 (at time t_1^g) and vehicle x receives it at time t_1 , within the time interval Δ_x (i.e., $\rho_{xy} <$ Δ_x). This context often occurs when traffic is sparse and the communication between two vehicles suffers no significant delay. In the second case, vehicle y generates message 2 at time t_2^g after vehicles x receives message 3, due to the communication delay in a busy V2X channel. If two vehicles are far from each other (i.e., the non-risk case), e.g., $T\hat{T}C'_{yy} = 20s$, increasing the time interval Δ_x with dozens of milliseconds in the first case does not impact the safety of the vehicles but can significantly reduce redundant data to transmit on the V2X communication channel. In the heavy traffic case, reducing the broadcasting rate on non-risk vehicles is vital to mitigate network congestion and allow the risk vehicles to access the channel. By contrast, if two vehicles are close to each other (i.e., the risk case), shortening the time interval Δ_x can suppress ρ_{xy} and increase the probability that vehicle x receives up-to-date information in time and thus improve the safety. As noted early, the lack of fresh information may create a wrong estimation at a receiver vehicle on the sender location. And then, this failure can threaten the safety of the surrounding moving vehicles.

A. PROBLEM FORMULATION

Since the safety of vehicle *x* depends on its relative location with surrounding ones, evaluating the AoI for the single pair *x*, *y* will underestimate the risk, i.e., *x*'s other neighbors can also cause a potential collision. An alternative approach is to evaluate the average AoI $\hat{\rho}_x$ based on the received beacon messages from its neighbor vehicles. Assume that there is a set of neighbor vehicles around *x* at the time *t* (denoted by N_x). Then, $\hat{\rho}_x$ can be calculated by:

$$\hat{\rho}_x = \frac{1}{|N_x|} \sum_{y \in N_x} \rho_{xy} \tag{6}$$



FIGURE 5. The illustration of our proposed architecture where it can be integrated into the V2X application layer to adjust time interval between packets for congestion control in the sensing layer.

The goal is to maintain the balance between (1) redundant data reduction, if any (i.e., lengthen Δ_x) and (2) the safety (*RIS_x*). The trade-off balance can be transferred into an optimization problem of minimizing the AoI, given the limited channel capacity. The function of minimizing the average AoI of all vehicles (denoted by *N*) can be expressed by:

$$\begin{array}{ll} \min_{f_x^t} & \sum_{x \in N} \hat{\rho}_x \\ \text{s.t.} & \sum_{x \in N} f_x^t < C_{max} \\ & f_{min} < f_x^t < f_{max}, \end{array} \tag{7}$$

where f_x^t denotes the broadcasting rate of beacon messages in vehicle $x, f_x^t = \frac{1}{\Delta_x}, C_{max}$ is the total channel capacity of V2X networks. f_{min} and f_{max} are the minimum broadcasting rate capacity and maximum broadcasting rate capacity, respectively, $f_{min} = \frac{1}{\Delta_{max}}, f_{max} = \frac{1}{\Delta_{min}}$. Due to the inverse relationship between f_x^t and Δ_x , increasing or decreasing Δ_x will impact directly the drop or the explosion of the broadcasting rate (i.e., f_x^t) accordingly. In the following section, we propose RTC+ that aims to use RIS_x and $\hat{\rho}_x$ to utilize the time interval Δ_x . Each vehicle in N can locally use this scheme to utilize their time interval.

III. RTC+: RISK ASSESSMENT AND PROACTIVE TRANSMISSION CONTROL

Figure 5 illustrates the architecture of our risk-based transmission control scheme, i.e., RTC+. RTC+ runs on the application layer and can be integrated into the V2X communication facility (i.e., OBU) of the vehicles. RTC+ consists of two modules. First, RTC+ launches RiskSCAN, an automated risk assessment module to evaluate whether there is a risk that threatens the safety of a vehicle (e.g., RIS_x). And then, based on the risk assessment output of RiskSCAN, RTC+ triggers RateCONTR, a rate control module to utilize the next time interval for sending beacon messages. The details of RiskSCAN and RateCONTR are presented as follows.

A. RISKSCAN: AUTOMATED RISK ASSESSMENT ALGORITHM AND MUTUAL VERIFICATION

Evaluating available information (e.g., received beacon messages) to determine whether a vehicle faces the risk of potential collision at the time t is the core of RiskSCAN. The output of RiskSCAN provides an additional metric for revising communication strategy to satisfy the key goal of V2X, the safety of the vehicle. Algorithm 1 shows the pseudocode of RiskSCAN. The inputs of RiskSCAN consists of a vehicle x's current GPS location (p_x^t) , estimated location \hat{p}_x^t . Initially, RiskSCAN considers vehicle x at the risk mode in default (line 2, $RIS_x^t = 1$). Due to the importance of having a reference object to measure risk, RiskSCAN selects the nearest vehicle – the car that affects x's safety directly – in the neighbor list of x (line 5). The vehicle reference is then used to estimate the tracking error \hat{e}_{xy}^{t} and time-to-collision $T\hat{T}C_{xy}^{t}$ (line 8). Finally, RiskSCAN estimates the value of vehicle x's risk by using Equation 5 (lines 9 and 14). However, the risk factor can rapidly change in a dynamic environment. To avoid using the potential outdated information, RiskSCAN periodically runs after every scanning period T_{scan} . The period T_{scan} can be adjusted in [0.5, 1]. When traffic is heavy, the lower bound of the range is used. Also, suppose the average Ageof-Information is longer than TTC_{min} (line 11). In that case, the network can be congested and RiskSCAN will grant the vehicle with a risk state to pave the way for proactive reaction in advance if necessary. Finally, if the vehicles stop, e.g., waiting for the red traffic light, $RIS_x^t = 0$ since there is no risk to the vehicles in this case. RiskSCAN estimation will trigger when the vehicles start moving.

Algorithm 1 Automated Risk Assessment Algorithm for	r
Vehicle x (RiskSCAN)	

	Data : $\hat{p}_x^t, p_x^t, \hat{v}_x^t, v_y^t, t, TTC_{min}$
	Result : RIS_x^t
1	Function $\hat{\text{RiskSCAN}}(\hat{p}_x^t, p_x^t, \hat{v}_x^t, v_y^t, t, TTC_{min})$
2	$RIS_x^t \leftarrow 1$; # default setting
3	$temp \leftarrow 0;$
4	Extract received beacon messages to build the neighbor list N_x ;
5	Find the nearest vehicle y (by location) in the neighbor list N_x [location];
6	$mj \leftarrow$ MutualVerification(N_x [opinion]) in Algorithm 2; # Major opinion
7	$\hat{e}_{XV}^t \leftarrow p_X^t - \hat{p}_X^t ;$
8	$T\hat{T}C_{xy}^{t} \leftarrow \frac{ \hat{p}_{x}^{t} - \hat{p}_{y}^{t} }{ \hat{v}_{x}^{t} - \hat{v}_{y}^{t} }; $ # Equation 4
9	$temp \leftarrow T\hat{T}C_{xy}^{t} - \frac{\hat{e}_{xy}^{t}}{ \hat{v}_{x}^{t} - v_{y}^{t} } - TTC_{min};$
10	$\hat{\rho}_x \leftarrow \frac{1}{ N_x } \sum_{y \in N_x} \rho_{xy};$
11	if $\hat{\rho}_x \geq TTC_{min}$ then
12	$RIS_{r}^{t} \leftarrow 1; \#$ Risk identified
13	else
14	$RIS_x^t \leftarrow (temp > 0) ? 1 : ((mj == 1) ? 1 : 0);$
15	end
16	Embed RIS_x^t into x's beacon messages;
17	return RIS_x^t ;

However, over-confidence in the risk assessment is another challenge. It is unsafe to assume that the risk assessment is exact in every situation. Vehicle x may fail to evaluate the potential risk if its sensors have been damaged. We propose a *mutual verification procedure* to mitigate the negative impact of this phenomenon as follows. First, vehicle x

embeds its risk assessment result into its subsequent beacon messages. Second, vehicle x randomly checks risk assessment from the neighbor vehicles' beacon messages within a range, e.g., 100m (as shown in Figure 5). If a majority of vehicles cast a risk evaluation (line 6), vehicle x's risk will be adjusted based on this consensus value (line 10). The detail of majority-based verification in line 6 is detailed in Algorithm 2. MutualVerification returns 1 if the total risk entries are greater than the total non-risk entries and 0 if otherwise. If there is no neighbor near vehicle x, the default opinion is set at zero (non-risk). The time complexity of RiskSCAN in the worst case, i.e., all vehicles N are vehicle x's neighbors, is O(N).

Algorithm 2 Majority-Based Verification for Self-Risk

1	Assessment on Vehicle <i>x</i>
	Data: N _x [opinion]
	Result: 1 if correct, 0 if otherwise
1	Function MutualVerification(N _x [opinion])
2	$isRisk \leftarrow 0; \#$ default opinion
3	$risk \leftarrow 0; \#$ Total risk entries
4	$nonRisk \leftarrow 0; \#$ Total non-risk entries
5	foreach <i>r</i> in <i>N_x</i> [opinion] do
6	if $r == 1$ then
7	risk + +;
8	end
9	end
10	$nonRisk \leftarrow count(N_x[opinion]) - risk;$
11	$isRisk \leftarrow risk > nonRisk ? 1 : 0;$
12	return isRisk;
_	

B. RATECONTR: ADAPTIVE TRANSMISSION CONTROL

After getting risk evaluation results, RTC+ runs RateCONTR to control the time interval Δ_x or sending rate $\frac{1}{\Delta_x}$. Algorithm 3 shows the pseudocode of RateCONTR. The inputs of RateCONTR are (1) the output of RiskSCAN, (2) the constant parameters such as k, Δ_{min} (3) the estimated variables inherited from RiskSCAN such as $\hat{\rho}_x$, N_x . The output of RateCONTR is the adjusted value of Δ_x . Primarily, RateCONTR will shorten Δ_x to increase sending beacon messages if the risk to vehicle x is explicit (lines 2 and 3). By contrast, RateCONTR lengthens Δ_x if there is no risk to vehicle x (line 4, 5). The decreasing value will be based on the balance between the prior Δ_x and the measured AoI. The parameter k is an adjustable variable, k = 0.9 in default. If the time interval reaches a threshold Δ_{min} , a safety control reaction can be activated (lines 7 and 8), e.g., deceleration, since this case means the vehicles are moving very near each other. For deceleration, we use the average time interval of the neighbor vehicles as vehicle x's new Δ_x (line 9). AverageTimeInterval in line 9 returns the average value of all prior time intervals of the neighbor vehicles embedded into the beacon messages.

Unlike RiskSCAN, RateCONTR periodically runs after every Δ_x . This aggressive rate control strategy has two advantages. First, RateCONTR can increase or decrease Δ_x in a short time to balance the data reduction and the safety control. Second, we can reuse many variables calculated in RiskSCAN, e.g., $\hat{\rho}_x$, without repeating many estimations.

Algorithm 3 Transmission Control Algorithm for Vehicle *x* (RateCONTR)

	· · · ·
	Data : RIS_x^t , $\hat{\rho}_x$, Δ_x^t , N_x , k , Δ_{min}
	Result : Δ_x
1	Function RateCONTR(<i>RIS</i> ^{<i>t</i>} _{<i>x</i>} , $\hat{\rho}_x$, Δ_x^t , N_x , k , Δ_{min})
2	if $RIS_x^t == 1$ then
3	$\tilde{\Delta}_x \leftarrow k \Delta_x^t$
4	else
5	$\Delta_x \leftarrow (1-k)\Delta_x^t + k\hat{\rho}_x$
6	end
7	if $\Delta_x == \Delta_{min}$ then
8	Activate the safety control mode (Deceleration);
9	$\Delta_x \leftarrow \text{AverageTimeInterval}(N_x[\text{interval}]);$
10	end

11 return Δ_x ;

Note that the running time complexity of RateCONTR is O(1) only, so the computation overhead is lightweight.

C. DISCUSSIONS ON OPTIMAL BROADCASTING RATE AND POSSIBLE PERFORMANCE GAP

The goal of our solution to find the optimal time interval Δ_x or the optimal broadcasting rate f_x^t for each vehicle at the time *t*. However, given the tracking error, there may have a gap to gain an accurate risk estimation.

Discussion 1: Optimizing the broadcasting rate of *N* vehicles can minimize their average AoI.

Remark: Optimizing the broadcasting rate of vehicles N aims to minimize the data transmission of the non-risk vehicles when the V2X networks are under congestion. The bandwidth release parts are then transferred to serve risk vehicles. With the same number of vehicles N, this distribution model can assist more receivers in getting beacon messages of the transmitters than the case of no distribution model applied. The average AoI is then minimized as a result of less influence by the network congestion.

Discussion 2: The optimal broadcasting rate of vehicle x, f_x^t , is a variable value.

Remark: Risk measurement of the time to collision is the key information reference to suggest an adjustment to Δ_x and then f_x^t . As shown in Equation 3 and Equation 5, the value of TTC TTC_{xy}^t and risk assessment result RIS_{xy}^t are inversely proportional to the gap distance between vehicle x and vehicle y. The gap is a variable value if the velocity of the pair vehicle xy is different. Therefore, vehicle x needs to periodically evaluate TTC and RIS_{xy}^t to adopt an optimal broadcasting rate f_x^t .

Discussion 3: The accuracy of the optimal value f_x^t is directly proportional to the accuracy of the risk measurement RIS_x .

Remark: As shown in Equation 5, the wrong assessment on a risk situation to the non-risk case can cause a potential collision. Worse, that can cause the suggestion for decreasing f_x^t is incorrect. Therefore, the accuracy of risk measurement RIS_x indicates the right decision for adjusting the value of f_x^t . Note that the risk assessment performance is to rely much on the observer's tracking capability, e.g., vehicle x. *Discussion 4:* The age of the optimal value of f_x^t is equal to the period for renewing RIS_x and updating f_x^t .

Remark: Due to high mobility, the TTC and RIS_x assessment value is periodically changed. The accuracy of the evaluations in Equation 5 and Equation 3 relies on the up-to-date information about the location and the velocity of the vehicles. As a result, using a value of f_x^t is only meaningful if RIS_x is periodically re-evaluated and f_x^t is updated accordingly.

D. TIME COMPLEXITY

With a set of vehicles N, the time complexity of Algorithm 1 is $O(|N|+|N_x|)$ in the worst case, where all vehicles are the neighbors of vehicle x. It includes Algorithm 2 to measure the neighbor opinions of the risk assessment, which requires $O(N_x)$. With the function of risk comparison and decrease/increase calculation of the time interval, the time complexity of Algorithm 3 costs O(1) only. In overall, the total time complexity of RTC+ is $O(|N| + |N_x| + 1) = O(|N|)$.

TABLE 1. List of three congestion control models.

Model	Meaning	Δ_x
RTC+	► Dynamic interval time based on risk assessment window of 1000ms.	Dynamic
3GPP rate control [38]	► Application layer packets arrive every 50ms + an exponential distribution with a mean of 50ms	50ms
Default setting of DSRC	► Application layer packets arrive every 100ms	100ms



FIGURE 6. The illustration of a typical urban road with an unsignalized intersection and six lanes. A road-side unit (RSU) to assist V2I.

IV. PERFORMANCE EVALUATION

This section evaluates RTC+ performance in comparison with several baseline congestion control models a such as (1) RTC+, (2) 3GPP rate control, (3) Default setting of DSRC standard. The details of the model are summarized in Table 1. In this work, we use Veins [37], an open-source simulation

TABLE 2.	Road ne	etwork, 1	traffic, a	and	communi	cation	simulation
configura	tion.						

Туре	Parameters	Value
	Road length	2km
Road network	Number of lanes	6
setting	Car-Following-Model	Krauss
	SUMO step length	1ms
	Carrier frequency	5.9 GHz
	Number of subchannels	2
	Subchannel size	12 RBs
C V2V	Transmission frequency	10MHz
C-V2A	Packet size	300 bytes
channel	Noise figure	9dB
setting	Shadowing variance LOS	3dB

framework with models for ETSI ITS-G5/ 3GPP standard C-V2X, to validate RTC+ performance and the baseline models.

For the traffic network and mobility, we use Simulation of Urban MObility (SUMO) [39], a microscopic and continuous traffic simulation package designed to handle large networks. SUMO can provide realistic traffic and mobility traces for vehicles. We create an urban road with six lanes at an unsignalized intersection, as shown in Figure 6. The traffic density is adjusted between 50 and 300 vehicles/km with four options to reflect the traffic cases: 1) 50 vehicles/km (low density); 2) 120 vehicles/km (medium density); 3) 200 vehicles/km (high density); and 4) 300 vehicles/km (congestion). The total simulation time is 5 minutes (300s). The other parameters for configuration are listed in Table 2.

For measurement evaluation, Packet Delivery Ratio (PDR) is the key metric to measure the success rate of transmitting beacon messages [26]. PDR is measured by the total received messages at the receiver vehicles over the total messages sent by the sender vehicles. The farthest distance between two vehicles to evaluate risk and PDR performance is 500m. For on-road safety assessment, we use Collision Risk (CR) metric to measure the total times of the time to collision between each pair of vehicles exceeds TTC_{min} . Finally, CBR is the metric to quantify the proportion of channel time under busy above the total observation time T.

In the first scenario, as the evaluation results shown in Figure 7, PDR performance of RTC+ varies with traffic density. In the low-to-heavy traffic (Figures 7(a) and 7(b)), our RTC+ can help to increase PDR up to 25%, compared with fixed broadcasting methods ($\Delta_x = 50ms$ or $\Delta_x = 100ms$). Unlike the two latter transmission modes, PDR performance of RTC+ is not substantially degraded by the increase of the vehicle density. Instead of using a fixed transmission period, RTC+ dynamically adjusts the vehicles' sending rate based on Time-To-Collision or risk assessment (distance, velocity of surrounding nearby vehicles). This rate control strategy is particularly helpful to reduce redundant transmission and congestion if the vehicles are moving far from each other. In heavy and congested traffic cases, as shown in Figures 7(c) and 7(d), both the



FIGURE 7. The Packet Delivery Rate performance of RTC+ in different traffic density: a) 50 vehicles/1km (Low traffic) b) 120 vehicles/1km (medium traffic); c)200 vehicles/1km (heavy traffic); d) 300 vehicles/1km (congested traffic).



FIGURE 8. The Collision Risk performance of RTC+ in different traffic density: a) 50 vehicles/1km (Low traffic) b) 120 vehicles/1km (medium traffic); c)200 vehicles/1km (heavy traffic); d) 300 vehicles/1km (congested traffic).



FIGURE 9. The Channel Busy Ratio to apply RTC+ in different traffic density: a) 50 vehicles/1km (Low traffic) b) 120 vehicles/1km (medium traffic); c)200 vehicles/1km (heavy traffic); d) 300 vehicles/1km (congested traffic).

systems with $\Delta_x = 100ms$ and our rate control can increase a higher PDR than that of $\Delta_x = 50ms$. This is because when many vehicles transmit simultaneously, decreasing sending rate (lengthening Δ_x) in a vehicle can increase the chance for the other vehicles to use the channel. We believe that, while the saving is not much if applying RTC+ for a single vehicle, equipping the system for every vehicle will make a significant difference in terms of bandwidth savings and congestion mitigation. In the worst case (300 vehicles/km as in Figure 7(d)), RTC+ still maintains a competitive PDR performance, compared with using a fixed Δ_x . Note that the inappropriate increase Δ_x (e.g., to 200ms) can threaten safety due to losing updates of the nearby vehicles. By contrast, the Δ_x reduction in RTC+ is carefully controlled by risk assessment which accounts for the safety guarantee.

To measure whether the reduction impacts the safety, we used the CR metric. As mentioned early, CR denotes the total times of the time to collision between each pair of vehicles exceeds TTC_{min} . As shown in Figure 8, RTC+ can reduce the collision risk in all four cases of traffic density

compared to using two fixed broadcasting intervals. Even at the high speed of the vehicles and high traffic density (Figure 8(d)), our system can assist in reducing up to 20% percentage of the collision risk (compared with the case of using $\Delta_x = 50ms$), a promising result. Note that, in congested traffic cases, the vehicles move near each other, so CR is high (if improper acceleration). Besides, many obstacles ahead in the congested area can cause NLOS tracking errors (i.e., e_{rv}^t) that indirectly contribute to a high CR. Regarding the channel usage, the results in Figures 9(a), 9(b), and 9(c) indicate that the rate control in RTC+ can reduce the ratio of channel overload around 10%-30%, compared with the case of using the baseline models. If a group of vehicles move in a region (on the highway) and aggressively broadcast the messages (due to the same risks), as the results shown in Figure 9(d), the channel can be overloaded after a period (100s). This reveals a limit of the rate control in a rare case, where many platoons are moving near each other. We argue that it is a challenge to avoid network congestion if many vehicles are at the same risk case and request the channel simultaneously.



FIGURE 10. The **Packet Delivery Rate** to request the aid of V2I in balancing the transmission requests: a) Testing with different Δ_X rate control tactic; b) Performance of RTC+ applied in V2V and V2I.



FIGURE 11. The impact of RTC+ to the system parameters: a) the distribution of broadcasting rate after running RTC+ in local vehicles (for V2V/V2I communications); b) computing time for RTC+ risk assessment in different traffic density scenarios.

An alternative method is to ask C-V2X V2I (if available) for help in balancing the transmission requests. In our testing (heavy traffic case), as results shown in Figures 10(a) and 10(b), using RTC+ on RSUs and V2I can increase PDR performance around 15%-28%, compared with using RTC+ with V2V only. The positive result comprehensively proves that the dynamic rate control of RTC+ can subtly tune the broadcast interval and utilize the channel resources effectively, even in heavy traffic. On the other hand, RTC+ can maximize the safety while guaranteeing the refreshing updates of sharing information (broadcasting rate).

The dynamic rate control of RTC+ impacts the broadcast interval Δ_x distribution. As the results are shown in Figure 11(a), unlike a fixed straight line in the cases of $\Delta_x = 50ms$ and $\Delta_x = 100ms$, the value of Δ_x of RTC+ is variable and adaptive, around 50ms if applying RTC+ with V2I or 78ms if applying RTC+ with V2V. Note that Δ_x is adjustable in the range $[\Delta_{min}, \Delta_{max}]$ which is [20, 200] in this simulation. The difference of mean value comes from the network capability of two network models where C-V2X V2I and V2I/RSU have significant advantages of efficient resource allocation. However, there is a remarkable deviation in both cases of the mean value. Strong flats on both sides indicate highly dynamic changes of adjusting broadcast intervals in RTC+ to adapt to the driving states. Generally, the changes to the left side of the mean value in Figure 11(a) denotes that RTC+ adjusts Δ_x to increase the refresh rate for capturing the risks. The left-most value indicates a rare case where many platoons of vehicles are moving near each other at high speed. The right-most value denotes



FIGURE 12. The illustration of how RTC+ assesses risks of the vehicles and dynamically adjusts their broadcasting rate accordingly. Each vehicle in this scenario has 20 neighbor vehicles in sharing sensing data.

the case when traffic is sparse. Finally, the running time of RTC+ for a single vehicle is negligible. As the results are shown in Figure 11(b), the computing time to run RTC+ is within several milliseconds only, even surrounding up to 20 neighbor vehicles. The performance is positive because the time complexity of RTC+ is O(|N|) only (Section III-D).

In practice, RTC+ can assist time-sensitive V2X applications (e.g., to help the vehicles to pass through unsignalized intersections) significantly by a robust risk assessment and Δ_x calibration. Since the vehicles demand highly dynamic data from the surrounding environment, such as the nearby vehicles, location, velocity, and heading, the goal is to obtain the smallest average AoI (i.e., $\hat{\rho}_x$) for maintaining the up-todate information for the vehicles. Given the limited channel capacity, if using RTC+, the vehicles moving near each other will have to access the channel with a higher broadcasting rate (short Δ_x) than the vehicles moving without neighbors or far from each other. This approach thus can serve the vehicles based on their urgent risk. Figure 12 illustrates how RTC+ assesses the urgency of the risk for each vehicle and dynamically adjusts their broadcasting rate. The vehicles moving away from nearby vehicles or stopping pose fewer threats to the safety of surrounding vehicles, so they can reduce the broadcasting rate to give away channel occupation for the vehicles approaching the intersections or accelerating to exit the area. In non-time-sensitive applications, the risk assessment (TTC) can be less strict (longer) than in the time-sensitive services. At this aspect, RTC+ is robust to work for different services. Generally, the rate control adjustment will create an opportunity to serve more vehicles simultaneously (e.g., for infotainment) or prioritize the radio resources/bandwidth for the vehicles under risk at most. Besides, the output of risk assessment and update period from RTC+ can be indirectly meaningful for the remote macroscopic traffic control models, e.g., estimating the areas with high risks for driving in real-time. Note that the Roadside Units (RSUs) can periodically collect such assessment and update sharing information to the remote center from

the broadcast beacon messages of the vehicles (line 16 of Algorithm 1).

V. CONCLUSION

Mitigating network congestion is essential to maintain the reliability of vehicular networks, particularly in the heavy traffic context. In this work, we present an adaptive risk-based transmission control scheme, namely RTC+, to dynamically adjust the broadcasting interval of beacon messages. RTC+ assesses surrounding risks by estimating the time to the collision to neighbor vehicles/obstacles. Based on the assessment, RTC+ can adjust the broadcasting interval to reduce the sending rate of non-risk vehicles while increasing the allocation for the risk vehicles. Our approach thus can minimize the congestion, which in turn, maintains the on-road safety of vehicular networks. The evaluation results show that our system can increase 25% on-time packet delivery rate, reduce 10%-30% channel usage, and mitigate 20% collision threats. The performance indicates significant advantages of our method over the methods of using the default configuration of broadcasting intervals in current vehicular networks.

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VAN-LINH NGUYEN (Member, IEEE) received the Ph.D. degree in computer science and information engineering from the National Chung Cheng University (CCU), Taiwan, in 2019. He currently works as a Postdoctoral Fellow with CCU. He is also an Assistant Professor with the Thai Nguyen University of Information and Communication Technology (TNU-ICTU), Vietnam. His research interests include network intelligence, edge intelligence, cyber security, and autonomous driving.



LAN-HUONG NGUYEN received the M.Sc. degree in computer science from the VNU University of Engineering and Technology, Vietnam, in 2016. She is currently pursuing the Ph.D. degree in computer science and information engineering with the National Chung Cheng University, Chiayi, Taiwan. Her research interests include vehicular networks, mobile edge computing, and network optimization.



JIAN-JHIH KUO (Member, IEEE) received the Ph.D. degree in computer science from the National Tsing Hua University, Taiwan, in 2014. He was a Postdoctoral Fellow with the Institute of Information Science, Academia Sinica, Taiwan. He is currently an Assistant Professor with the Department of Computer Science and Information Engineering, National Chung Cheng University, Taiwan. His research interests include softwaredefined networking, mobile edge computing, and cloud computing.