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Context-Aware Navigation Protocol for Safe Driving in Vehicular Cyber-Physical Systems

Bien Aime Mugabarigira, *Student Member, IEEE*, Yiwen Shen, *Member, IEEE*, Jaehoon Jeong, *Member, IEEE*, Tae Oh, *Senior Member, IEEE*, and Han-You Jeong, *Member, IEEE*

***Abstract*—A connected network of automated vehicles on roads can increase the driving safety of driverless vehicles (i.e., autonomous vehicles). The critical level of dangerous situations on the road while driving can be increased by the speed, orientation, and traffic density of the vehicles involved. Therefore, there is a need for a maneuvering mechanism that handles both the current driving vehicle and the oncoming vehicles headed toward an emergency zone (e.g., road hazard and road accident spot). In this paper, we present a context-aware navigation protocol (CNP) that enhances the safety of vehicles driving in urban roads. Firstly, CNP includes a collision avoidance module that builds on both vehicular networks and on-board sensors to track vehicles' behaviors, and this module analyzes the driving risks to determine the necessary maneuvers in dangerous situations. Secondly, CNP establishes a collision mitigation strategy that limits the severity of collision damages in hazardous road during non-maneuverable scenarios. We conducted a theoretical analysis as well as extensive simulations to prove and evaluate the effectiveness of CNP. The results show that CNP can reduce communication overhead from a baseline scheme by up to 60% while the risk of road collisions is less than 5%.**

***Index Terms*—Autonomous vehicle, context-aware navigation, vehicular networks, driving safety, path planning.**

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Bien Aime Mugabarigira is with the Department of Electrical and Computer Engineering, Sungkyunkwan University, Suwon 16419, South Korea (e-mail: bienaime@skku.edu).

Yiwen Shen is with the School of Global Studies, Kyungsung University, Busan 48434, South Korea (e-mail: chrisshen@ks.ac.kr).

Jaehoon Jeong is with the Department of Computer Science and Engineering, Sungkyunkwan University, Suwon 16419, South Korea (e-mail: pauljeong@skku.edu).

Tae Oh is with the School of Information, Rochester Institute of Technology, Rochester, NY 14623 USA (e-mail: tom.oh@rit.edu).

Han-You Jeong is with the School of Electrical and Computer Engineering, Pusan National University, Busan 46241, South Korea (e-mail: hyjeong@pusan.ac.kr).

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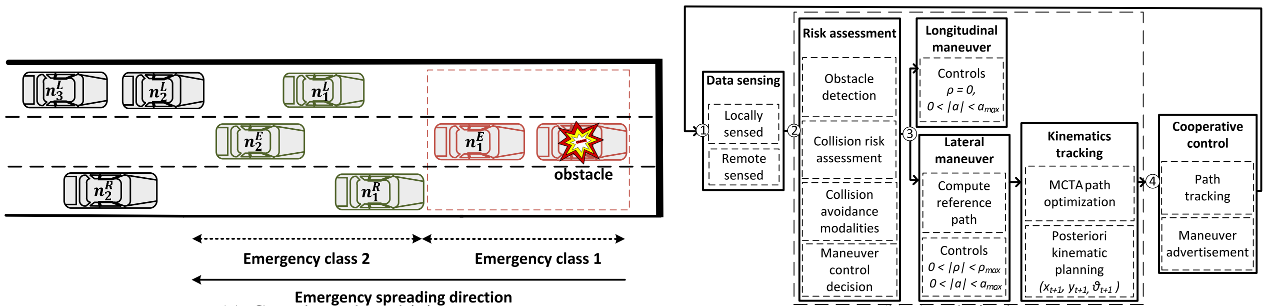
I. Introduction

VEHICLE networking enables interoperability among vehicles, drivers, pedestrians, and road network infrastructures, which directly impacts the transportation safety [1]. Driverless vehicle technology has attracted increasing research interest in both academia and industry due to its potential to substantially enhance vehicular transportation in terms of accessibility, safety, and convenience. One of the most anticipated benefits of self-driving vehicles is the lack of a driver's errors that lead to accidents. Human drivers are responsible for 94% of critical events that cause crashes, while the environment, vehicles, and unknown-related causes cumulatively account for the remaining 6% [2]. The expected increase in driving safety is one of the main motivations to invest in autonomous driving research.

Although autonomous vehicles promise to improve driving safety, they face a lack of public acceptance stemming from safety concerns [3], [4], and significant research initiatives have gone toward addressing those concerns. Over the past three decades, a vehicle has reached a new technological maturity with driver assistance systems (DAS) [5]. These include driver warning systems (e.g., night vision, lane departure, and adaptive cruise control) and automated driver-system cooperation systems (e.g., low-speed automated driving and forward collision prevention). However, human driving errors can be fully eradicated with the introduction of autonomous driving. Despite recent research efforts, there is still a need of safety enabling systems for vehicles to autonomously cooperate in assessing driving risk outside of the line of collision. These systems need to safely guide vehicles to avoid collisions in the road without jeopardizing their safety and with minimal or no effect on their overall trajectory. A system that integrates road infrastructures with vehicles to have computing, communication and control abilities is commonly known as vehicular cyber-physical system (VCPS) [6].

This paper presents a context-aware navigation protocol (CNP) to increase driving safety in VCPS. The CNP is a protocol that solves a complex urban driving scenario as shown in Fig. 1(a). When a vehicle abruptly stops in the middle of a lane, it creates an unexpected driving situation



(a) Complex urban driving. (b) A solution's steps.

Fig. 1. An illustration of the driving complexity with the presence of an obstacle in a roadway.

for any following vehicles. The reaction of e_1 may impact the driving of either e_2, l_1 or r_1, which in turn will need to react, thereby creating a more complex driving scenario. We name "emergency zone" the part of the road where the vehicles need to maneuver to bypass an obstacle and those vehicles are "emergency vehicles". This system distinguishes two classes of emergency vehicles. A directly concerned vehicle e_1 is emergency class 1 while indirectly affected ones are emergency class 2.

Through modular steps described in Fig. 1(b), CNP provides a relevant driving solution for vehicles driving in hazardous situations. First, a data sensing which consists of sending and receiving the self-sensed and remote-sensed mobility information according to the CNP communication protocol described in Section IV-A. Second, a risk assessment which analyzes the received data to identify the abnormal behavior in the driving environment and collision avoidance modalities. Third, a path maneuver that defines the appropriate trajectories changes either longitudinally or laterally across the road for the concerned vehicles. Lastly, a path tracking, which keeps the maneuver path until the maneuvered vehicle reaches the target without deviation. The path maneuvers are shared with the neighbors via communication for the awareness purpose.

The major contributions of this work are summarized as follows:

- **The design of networked context awareness navigation protocol (CNP)**: It is a protocol that uses an IPv6 Neighbor Discovery (ND) option to convey vehicles' mobility information. This protocol enables cooperative sensing through light-weight message sharing. It renders ambient awareness by quickly analyzing sensed data to determine anomalous behaviors such as abrupt slowing and sudden lane changes. Upon the detection of emergency risks, the CNP takes further measures to quickly adjust a vehicle's trajectory (see Section IV).
- **Lane quality-based collision avoidance**: We develop a lane metric indicating the state of lane collision risk prior to emergency vehicle maneuver decision. It permits vehicles to maneuver towards the safest lane and lets their maneuver have the minimal impact on the overall road safety. Through the probabilistic collision risk assessment, we deduce the best maneuver for a vehicle in risk of collision with an obstacle in the road (see Section IV).
- **A simulation-based evaluation of the proposed model**: In order to demonstrate the efficiency and usefulness of the proposed model in this paper, we implemented a vehicular simulation and evaluated it under various conditions. The evaluation results show that the CNP can reduce the risk of collision with a little communication overhead compared to the baselines (see Section V).

Note that this is an improvement of the preliminary work presented in our previous paper [7].

The rest of this paper is organized as follows. Section II summarizes the previous work related to our study. Section III makes the notation definitions and assumptions used in this paper, and defines the problem that this work solves as well. Our network-based vehicle tracking mechanism is described in details in Section IV. Section V validates our CNP mechanism by comparing it with other sensing and tracking mechanisms. Finally, we conclude this paper along with future work in Section VI.

II. Related Work

This section summarizes the previous work focusing on the driving safety for connected and automated vehicles.

Beginning with the DARPA urban challenge in 2007 [8], several studies have attempted to design autonomous vehicles that can be used in real driving. Autonomous vehicles can make meaningful assessments according to the significance of any perceived data, and they can also predict future events and make proactive decisions to avoid accidents [9]. Proper awareness and assessment mechanisms are needed to respond to the wide variety of situations that arise in real road traffic.

To avoid collisions in autonomous driving, several mechanisms have been proposed, including both sensor-based and non-sensor-based approaches. A typical sensor-based mechanism is the lane-level beacon-less, infrastructure-less, and GPS-less cooperative collision avoidance (BIG-CCA) framework proposed by Chen and Chou [10]. This mechanism uses V2V communication to warn vehicles in the same lane of any danger. Another model proposed by [11] uses a platooning paradigm to model accidents involving a platoon equipped with a warning notification system. A parallel autonomy framework uses a nonlinear model predictive control to compute a safe trajectory for an automated vehicle based on human input [12]. The cooperative collision avoidance (CCA) systems enable vehicles to cooperate to achieve driving safety.

CCA mechanisms include platooning [13], a networked collision avoidance system [14], an agent-based situational assessment [15], and a feature-based cooperative perception

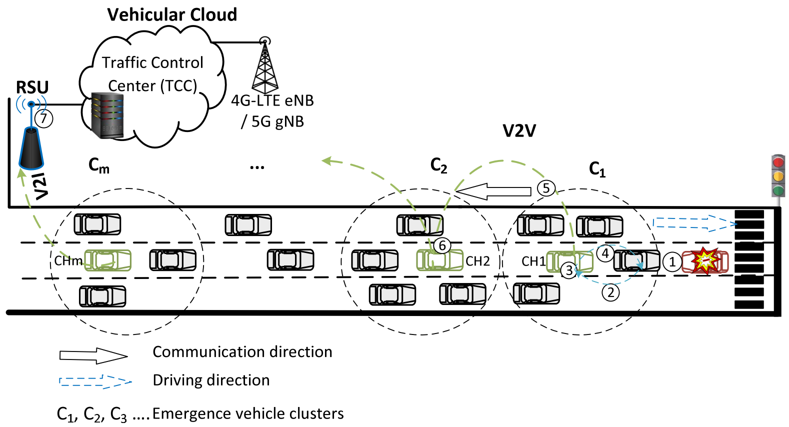


Fig. 2. A target model for handling an emergency situation with CNP.

framework (F-Cooper) [16]. In the platooning, vehicles follow the same route and drive closely enabling them to cooperate through low latency data delivery. The networked collision avoidance system (NCAS) allows vehicles to work together by broadcasting driving information over a shared channel. A central controller collects the driving data and manages vehicles that behave according to an agent-based modeling [15]. F-Cooper is an object detection model that was proposed to remedy the limitations caused by network bandwidth and the constraints of autonomous applications. The cooperative adaptive cruise control proposed by [17] regulates the interdistance between vehicles to achieve string stability in a networked control system.

Junietz et al. studied an approach to define the criticality metrics that validate the safety of automated driving [18]. Using the model predictive control (MPC), they define the driving required in a specific situation for real time trajectory planning and control. Feng et al. reduced the required testing miles required to validate the driving safety performance in autonomous vehicles by adversarial adjustments to the naturalistic driving environment [19]. The model predictive instantaneous safety proposed by [20] analyzes the closeness to collision to guarantee safety in terms of time to collision. Li et al. proposed a collision avoidance (CA)-based risk assessment where metrics such as time to collision, time to stop, and time to react are combined to define the safety status of driving vehicles [21]. Unlike the prior models, our context-aware navigation protocol provides a possibility to preemptively avoid collision with out-of-sight obstacles through wireless communication by guiding them towards a safe lane. The CNP includes an emergency path planning and tracking strategy based on a minimal contour tracking algorithm proposed in [22] to define the path maneuver for vehicles both in line-of-sight and out-of-sight of the obstacle in the road.

III. Problem Formulation

We designed the CNP with two-fold safety oriented objective such as collision avoidance and collision mitigation. The collision avoidance model ensures that the autonomous vehicles drive safely when they are faced with obstacle(s) in a road segment. Meanwhile, the collision mitigation model, which is proposed by this paper, guarantees a minimal collision impact for unavoidable accident scenarios. In this section, we describe in detail the notations, assumptions, and the problem targeted by our model.

A. Notation Definitions

Fig. 2 shows a networked emergency processing architecture. In this paper, we adopt a communication protocol wherein vehicles are grouped into m clusters $C = \{C_1, C_2, \ldots, C_m\}$; the cluster head (CH) is the leader of the cluster. Our model uses the K-mean clustering approach [23] where CH is a cluster-head vehicle which makes the smallest intracluster Euclidean distance from its cluster members. CHs share driving information with each other via Vehicle-to-Vehicle (V2V) communication. Meanwhile, the Traffic Control Center (TCC) maintains traffic statistics and communicates with the vehicles via Vehicle-to-Infrastructure (V2I) communication.

Let an emergency event be any unusual behavior that happens on the road that degrades the safety of vehicles. The emergency driving process described in Fig. 2, which avoids collisions of vehicles, consists of the following steps:

Step 1: An emergency event suddenly occurs in the road becoming a driving obstacle.

Step 2: A cluster member detects and broadcasts the obstacle information to its neighbors.

Step 3: The CH receives and evaluates this information, to identify the obstacle collision risk. It calculates a required maneuver for each vulnerable member.

Step 4: The CH then informs the members in step 3 of the obstacles and the appropriate maneuvers.

Step 5: The safety information is shared with neighboring clusters via their CHs.

Step 6: Each CH will take proactive steps to address any safety issues.

Step 7: Through V2I communication, the TCC receives and maintains up-to-date global mobility statistics and calculates safe trajectories for vehicles in the road network.

Now we formulate equations and functions for our CNP. The nodes in vehicular ad hoc networks (VANET) follow a very well-structured path organized in roads and their sub-roads, or lanes. CNP considers a road segment e_{ij} with the number of lanes $l > 1$, where N vehicles in a set $\mathcal{V}$ are traversing the road segment from entrance i toward exit j intersections at a particular instant time t. At time t, a vehicle $n_i, i = \{1, \ldots, N\}$ state is defined as

$$s = \left[x_i \ y_i \ v_i \ \theta_i\right]^T, \tag{1}$$

where (x_i, y_i) is its position, v_i is its speed, θ_i is its moving direction, and its trajectory control input is defined as

$$u = \left[\rho_i \ a_i\right]^T, \tag{2}$$

where the steering angle is ρ_i and acceleration is a_i. For a vehicle with a distance L between two axles of a wheelbase [22], its θ_i can be derived by

$$\dot{\theta}_i = \frac{v_i}{L}\tan(\rho_i). \tag{3}$$

The dynamic that specifies n_i's future behavior is defined by the following nonlinear differential equation:

$$\dot{s} = f(s, u(t)). \tag{4}$$

A vehicle at risk of collision is an *emergency vehicle*, n_{em}, and the one it is about to collide with is an *obstacle*, n_{ob}. A lane where n_{em} is positioned is an *emergency lane*, L_E. The n_{ob} can either be moving (i.e., moving extremely slowly) or resting (i.e., completely stopped). A resting obstacle can only be defined by its position $\left[x_{ob} \ y_{ob}\right]^T$.

B. Assumptions

We take into consideration the following assumptions in our CNP, which investigates the traffic flow λ for a road segment in a defined time slot:

- Each vehicle is allowed to share both local and remote kinematics information.
- Periodically, each vehicle broadcasts its own mobility information, such as speed, direction, and position, which allows the cluster header to identify its kinematics in real time.
- CNP assumes that a non-sliding vehicle's wheels roll with non-holonomic constraints, thus allowing a vehicle's maneuvers to be defined without the impacts of friction.
- Vehicles in a road segment are assumed to be moving in the same direction from intersections $i \rightarrow j$ or at rest. A vehicle is said to be at rest when its speed $v = 0$.
- An acceleration of a vehicle a has a minimum and maximum bound, i.e., $a \in [a_{min}, a_{max}]$, where a_{min} and a_{max} are the lowest and highest accelerations attainable by a vehicle, respectively.
- A steering angle of a vehicle ρ has a minimal and maximum bound, i.e., $\rho \in [\rho_{min}, \rho_{max}]$, where ρ_{min} and ρ_{max} are the minimal and maximal angles, respectively, that a vehicle can steer its wheels.

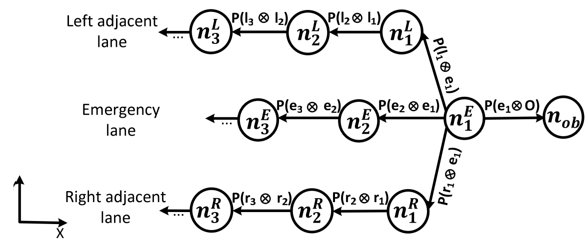


Fig. 3. A collision probability graph for an emergency vehicle.

C. Problem Definition

1) Emergency Driving Handler: We illustrate a road network as a graph $G = (\mathcal{V}, E, c)$ constructed by a set of vehicles $\mathcal{V}$ that defines the vertices, and a set of edges E with a cost equivalent to the collision risk associated with a neighboring vehicle. The function $c : E \rightarrow \mathbb{W}$ assigns the cost to each edge as shown in Fig. 3. Given a graph $G = (\mathcal{V}, E, c)$, CNP computes a feasible lateral driving path for a vehicle when an obstacle is identified in its safe driving direction.

Problem 1 (Emergency Path Planning Problem): It consists of determining a path P_{em} for a vehicle $n_i \in \mathcal{V}$ such that the collision probability P_{col} associated with the relative kinematics of adjacent vehicles shall always be low during the entire maneuver time Δ_t.

Let $v_p(t)$ be the speed of the front vehicle n_p (called the parent vehicle) driving or resting ahead and $v_c(t)$ be the speed of the following vehicle n_c (called the child vehicle) at time t. Let Δ_t be the required maneuver change time of the following vehicle n_c. Let β be the Euclidean distance between vehicle n_p and n_c.

The collision probability P_{col} for two vehicles n_p and n_c during a maneuver time Δ_t is calculated as

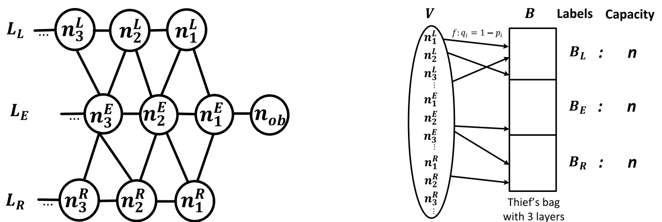
$$P_{col}\left[\int_t^{t+\Delta_t} v(t)\,\mathrm{d}t + \epsilon_v \geq \beta\right], \tag{5}$$

where $v(t) = |v_c(t) - v_p(t)|$ is the relative speed, and $\epsilon_v \sim \mathcal{N}(0, \sigma)$ is the speed measurement error, $\sigma = \{1, 2, 3, \ldots, 10\}\,km/h$. The trajectory distance $d_i(t)$ of an emergency vehicle n_i during the maneuver process is defined as

$$d_i(t) = \int_t^{t+\Delta_t} \left\{v(t) + \int_t^{\tau} \left(a_i u + \epsilon_a\right)\mathrm{d}u\right\}\mathrm{d}t, \tag{6}$$

where $v(t)$ is the speed function, u is the maneuver control input according to (2), a is the acceleration, and ϵ_a is the acceleration error at time t.

2) NP-Hardness of Emergency Driving Problem: The solution of Problem 1 defines a safe path of n_1^E in a situation shown by Fig. 4(a). The forward driving of n_1^E will collide with an obstacle n_{ob} and can collide with n_2^E if it abruptly slows its speed down. Moving to the left lane can cause a collision with n_1^L and its maneuvers to the right lane can cause a collision with n_1^R. Whatever the driving decision of n_1^E is, it can affect the maneuver of at least one among its adjacent vehicles. Suppose that n_1^E moves to the left lane by stimulating the neighbor n_1^L's maneuver decision. Any maneuver of n_1^L should also consider the kinematics of its adjacent vehicles n_2^E



(a) An original problem (b) A reduced problem

Fig. 4. An illustration of NP-Hardness for the emergency driving problem.

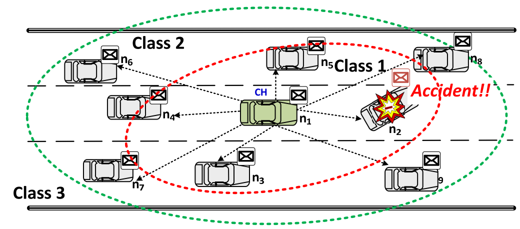


Fig. 5. Cluster-head-coordinated dynamic maneuver planning.

and n_2^L. Those decisions can also result in the involvement of exponentially large-space searching to find out a safest path for each vehicle in either a road segment or intersection.

Given a sequence of vehicles, each at the risk of colliding with neighbors, the decision-making problem to find vehicles' safe maneuvers is an NP-complete problem. Assume that the road e_{ij} is a thief's bag with three layers B_L, B_E, and B_R each with capacity n, respectively, representing the left lane of the emergency lane, the emergency lane and the right lane of the emergency lane, as shown in Fig 4(b). We demonstrate that the knapsack problem [24] in Fig. 4(b) is a special case of the emergency path planning problem in Fig. 4(a). The knapsack problem is a well-known NP-complete problem. It is infeasible to find a polynomial-time algorithm that can safely control the maneuvering of many vehicles on the road. By knowing the safe lane quality among adjacent vehicles (defined in Section IV-C) as a weight for knapsack, linear program (LP) relaxation can alleviate the difficulty of the problem of emergency maneuver decision. The emergency driving decisions set S^* that maximizes the safe driving profit, is defined as function

$$\begin{aligned} f: \quad & V \rightarrow B \\ \text{such that } & S^* \leftarrow \arg\max \sum_{i=1}^{N} S_i, \end{aligned} \tag{7}$$

where S_i is the safe lane quality of each vehicle as a safety metric in the maneuver lane computed according to (12) and (13) in Section IV-C.

3) Minimized Collision Scenario: Our approach minimizes the collision impact in two ways. First, we ensure that the colliding vehicles crash with as little energy transfer as possible. Second, we minimize the number of vehicles affected by this accident through collaborative maneuver control.

Problem 2 (Collision impact minimization problem): When a child vehicle n_c detects a dangerous situation that is too close to be avoided, the collision impact shall be minimized so that the involved vehicles may suffer minimal damage.

Equivalent Energy Speed (EES) [25] is computed as follows when a child vehicle n_c collides with a front, parent vehicle n_p:

$$EES = \hat{\upsilon}_c - \upsilon_c = \frac{2m_p}{m_c + m_p}(\upsilon_p - \upsilon_c), \tag{8}$$

where m_c and m_p are the masses of n_c and n_p, respectively, υ_c and υ_p are the speeds of n_c and n_p, respectively, and $\hat{\upsilon}_c$ is the speed of n_c after collision, i.e., resultant speed.

In Section IV, we discuss how our scheme computes the road collision risks and deduces the proper maneuvers.

IV. Sensing and Perception Module

A. CNP Communication Protocol

The proposed CNP enhances driving safety by offering a light-weight driving information sharing method. This model has two types of messages that serve as IPv6 neighbor discovery (ND) options for the CNP services: the cooperation context message (CCM) and the emergency context message (ECM). CCM enables cooperative driving through the exchange of a vehicle's mobility information (e.g., speed, position, and direction) and its driving actions (e.g., braking and accelerating) with its neighbors. ECM notifies a vehicle's neighbors of emergency situations (e.g., accidents). This protocol gives higher priority to the ECM than the CCM in the message delivery process of vehicles.

Due to ECM's higher priority than CCM, a vehicle can take immediate action in response to an emergency situation. As shown in Fig. 5, if there is an obstacle in a road, an ECM message is sent to adjacent vehicles via a channel for safety purposes. We advocate the use of multiple DSRC service channels that prioritize ECM safety messages. We employ vehicle clustering wherein cluster head (CH) leads cluster members' safety decisions. CH orchestrates the emergency maneuvers of its members to avoid collisions. Both CCM and ECM transmissions are performed with IPv6 packets in IEEE standard 802.11-OCB network mode [26]. The members' maneuvering plans are decided by a collision probability based risk assessment which will be defined in Section IV-B.

B. Probabilistic Risk Assessment

Dynamic road traffic participants drive within uncertain locations, directions, and speeds. The maneuvering decisions of a vehicle in such a road are computationally uncertain. The CNP determines the appropriate maneuverable driving lane depending on the collision probability of the emergency vehicle.

We define the "*collision probability*" as the risk that a moving vehicle will collide with an obstacle ahead in a road. The collision risk is generally calculated as time to collision T_c through the relative kinematics of adjacent vehicles on the road [25]. The minimal maneuverable time to collision T_{cmin} is reached when a vehicle maximally accelerates toward the obstacle, and the maximal maneuverable time to collision T_{cmax} is when it minimally accelerates (i.e., maximally decelerates) toward the obstacle. Considering that the collision risk of an n_{em} is uniformly distributed within $T_c \in [T_{cmin}, T_{cmax}]$. The collision probability that an n_{em} will collide with n_{ob} is computed as follows:

$$P(n_c \otimes n_p) = \begin{cases} 1, & \text{if } T_c \leq T_{cmin}, \quad (9a) \\ 0, & \text{if } T_c \geq T_{cmax}, \quad (9b) \\ P_{c,p}, & \text{otherwise}, \quad (9c) \end{cases}$$

where (9a) means that a child vehicle n_c will certainly collide with its parent vehicle n_p, (9b) suggests that n_c is safely driving away toward n_p, and (9c) defines a collision probability (denoted as $P_{c,p}$) that n_c is driving toward n_p which is computed as follows:

$$P_{c,p} = 1 - \left(\frac{T_c - T_{cmin}}{T_{cmax} - T_{cmin}} \right). \tag{10}$$

Vehicles in an emergency driving situation can collide with other vehicles not only in a line-of-sight unsafe range, but also in a non-line-of-sight but unsafe range [27]. Consider an emergency vehicle n_1^E driving towards n_{ob} as shown in Fig. 3. Let $\mathcal{V}_L = \{n_1^L, n_2^L, \ldots, n_u^L\}$, $\mathcal{V}_E = \{n_1^E, n_2^E, \ldots, n_v^E\}$, and $\mathcal{V}_R = \{n_1^R, n_2^R, \ldots, n_w^R\}$ be vehicles sets in the left L_L, emergency L_E, and right L_R lanes respectively. The emergency graph G depicted in Fig. 3 enables the CH to determine the lateral maneuver of n_1^E toward the least-risk lane, which is a lane with the minimum collision probability.

C. Link Quality-Based Maneuver Lane Selection

Considering the collision risk events $(n_1^L \otimes n_1^E)$, $(n_2^L \otimes n_1^L), \ldots, (n_u^L \otimes n_{u-1}^L)$, respectively, for children $n_1^L, n_2^L, n_3^L, \ldots, n_u^L$ to collide with their parents n_1^E, n_1^L, $n_2^L, \ldots, n_{u-1}^L$, let their corresponding probabilities be p_1, $p_2, \ldots, p_u$. Let the events $(n_1^R \otimes n_1^E)$, $(n_2^R \otimes n_1^R), \ldots$, $(n_{w-1}^E \otimes n_w^R)$, respectively, for children $n_1^R, n_2^R, n_3^R, \ldots, n_w^R$ to collide with their parents be $n_1^E, n_1^R, n_2^R, \ldots, n_{w-1}^R$ and let their corresponding probabilities be $p'_1, p'_2, \ldots, p'_w$. The n_1^E maneuvers toward a lane with better quality. Let the safe probability q_i of a vehicle n_c driving toward another vehicle n_p be

$$q_i = 1 - p_i, \tag{11}$$

where p_i is the collision probability of event $(n_p \otimes n_c)$. Consequently, we deduce the **safe lane quality** of every lane of the road.

Definition 1 (Safe Lane Quality): Let the ***Safe Lane Quality*** *S_{Lx} of a given road lane L_x be a lane metric that indicates the state of lane safety during the emergency driving decision.* The safe lane quality of the left lane will be computed as follows:

$$S_L = \prod_{i=1}^{u} q_i, \tag{12}$$

and the safe lane quality towards the right lane is computed as:

$$S_R = \prod_{i=1}^{w} q'_i, \tag{13}$$

Algorithm 1 Emergency Maneuver Lane Determination

1: **function** DETERMINE_MANEUVER_LANE($G = \mathcal{V}, E$) ▷ G is the graph constructed by a set of vehicles $\mathcal{V}$ where each vehicle is identified by its position and speed
2: $n_p \leftarrow n_1^E$ ▷ initialize the parent node n_p to the vehicle n_1^E most risky to collide with n_{ob}
3: **for** each vertex v in $\mathcal{V}_{np}$ **do**▷ $\mathcal{V}_{np}$ is the vertexes set of n_p's children
4: **if** $n_c \neq null$ **then** ▷ Compute the edge cost when the current vertex has a predecessor
5: $T_c \leftarrow Compute\_Time\_To\_Collision(n_c, n_p)$
6: $P_{c,p} \leftarrow Compute\_Probability(T_c)$
7: $n_{c.p} \leftarrow P_{c,p}$ ▷ Assign the collision probability as the metric of each graph edge cost
8: **end if**
9: **end for**
10: $L_x \leftarrow 0$ ▷ Candidate maneuver lane index which varies from 0 to 2 for a three-lane road segment
11: $Q_{lane} \leftarrow 0$ ▷ Maneuvers toward the lane which has the greatest value of lane quality Q_{lane}
12: **for** each lane l in L **do** ▷ L is a set of road lanes and check the neighboring lanes of the defected lane that may be two elements (right and left lanes), or only one lane side
13: $Q_l \leftarrow Calculate\_Lane\_Quality(\mathcal{V})$
14: **if** $Q_{lane} < Q_l$ **then**
15: $Q_{lane} \leftarrow Q_l$
16: $L_x \leftarrow l$
17: **end if**
18: **end for**
19: **return** L_x
20: **end function**

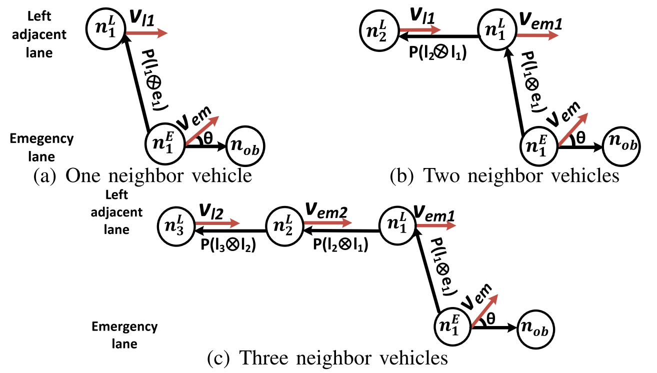
where q_i is the safe probability for n_p and n_c in the left lane, and q'_i is the safe probability for n_p and n_c in the right lane.

An n_1^E's collision avoidance maneuver follows the algorithm 1. Line 2 of Algorithm 1 initializes the parent node with n_1^E. The while loop in lines 3-9 assesses the risks of the graph G nodes with the parent-child relationship. Lines 4-8 calculate the collision risks among the adjacent vertices, and then assign a risk cost to the edge (n_c, n_p) in terms of collision probability according to (10). Lines 10-11 initialize the maneuver safe lane cost and n_1^E should maneuver to the lane with maximal safety. Lines 2-18 determine and compare lane qualities to choose the best lane. n_1^E will steer toward the lane returned by line 19.

Given the safe lane qualities S_L and S_R in the left and right lanes respectively, the decision of the lane (denoted as L_x^*) for maneuvering emergency vehicles in adjacent lanes is computed as follows:

$$L_x^* \leftarrow \max_{L_x \in \{L,E,R\}} (S_L, S_E, S_R). \tag{14}$$

Calculating an emergency vehicle's maneuvers is time critical. The complexity of the CNP maneuver planning algorithm is $\mathcal{O}(Nl)$. This complexity increases with the number of vehicles N driving in the defective road and the number



(a) One neighbor vehicle (b) Two neighbor vehicles

(c) Three neighbor vehicles

Fig. 6. Expansion of a collision probability graph for an emergency vehicle n_1^E toward the left lane L_l having multiple vehicles.

lanes l. To remedy this, we make a trade-off between the optimal risk assessment and the assessment time.

Fig. 6 illustrates a scenario for lane change of an n_1^E avoiding collision with n_{ob}. Considering it maneuvers towards the left lane, Fig. 6 shows possible scenarios that may arise.

- In Fig. 6(a), n_1^E bypasses n_{ob} without affecting the trajectory planning of existing vehicles on the maneuver lane. This often happens on roads with low vehicle density.
- In Fig. 6(b), n_1^E bypasses n_{ob} by affecting only the trajectory of its adjacent vehicles. This typically happens when vehicle n_1^L needs to either accelerate, decelerate or change lane in order to create enough space for n_1^E to avoid an accident.
- In Fig. 6(c), n_1^E affects the trajectories of multiple adjacent vehicles when bypassing n_{ob}.

The following section will discuss in detail how the CNP plans emergency paths for vehicles.

D. Emergency Maneuver

1) Emergency Path: Vehicles are sequentially maneuvered to avoid accidents in the road. Sequentially within the maneuver lane, CNP assesses the collision risk to make sure that an emergency vehicle n_{em} will safely access the lane without degrading the safety of the existing driving vehicles. CNP handles emergency driving, starting with the closest vehicle to the obstacle toward the rear vehicles. CNP defines the timely maneuver path of n_{em} from its contour area, in a way that guarantees the other vehicles' safety. Please refer to Appendix A, available in the online supplemental material, for the detailed path maneuver. Vehicles are laterally maneuvered to avoid any possible collisions with an obstacle n_{ob}. Longitudinal changes are only made when lateral maneuvers are not feasible toward other lanes. In the case of a reckless cut-in maneuver, our CNP mechanism will enable a vehicle to identify such an obstacle and quickly broadcast it among the driving vehicles, thus creating a preparedness to react to it. We prioritize the maneuver by changing lanes to enable vehicles to keep on their trajectories despite the obstacle in the road. However, for non-maneuverable vehicles, we enable vehicles to break or collide with as small energy as possible to limit damages.

TABLE I
SIMULATION CONFIGURATION

Parameter	Description
Road network	2 km road segment from entrance intersection i through exit intersection j.
Lambda λ	Vehicle injection rate is from $0.2 \sim 0.8$.
Driving Speed (v)	$v = 20 \sim 140$ km/h.
Acceleration/deceleration	Vehicle acceleration a ranges $[a = -6 \sim 6] m/s^2$.
Acceleration Error	$\epsilon = -1 \sim 1$ meters per second square.
ECM Transmission Rate	Frequency of safety information transmission. Default is 10 packets per second.

2) Collision Strength Minimization: For the unavoidable collision situation, a collision strength minimization mechanism is needed to minimize the energy transfer between the colliding vehicles, thus reducing damages. The severity of a collision is proportional to the masses of two colliding vehicles and their corresponding speeds. Assuming that an emergency vehicle n_{em} with speed v_{em} and mass m_{em} collides with an obstacle n_{ob} with speed v_{ob} and mass m_{ob}, the collision strength calculation is made using their Equivalent Energy Speed (EES) [25] calculated according to (8). The derivation of the collision strength minimization can be found in Appendix B, available in the online supplemental material.

Up to now, we have described in detail the theoretical mechanism of the CNP. In the next section, we will explore the performance evaluation.

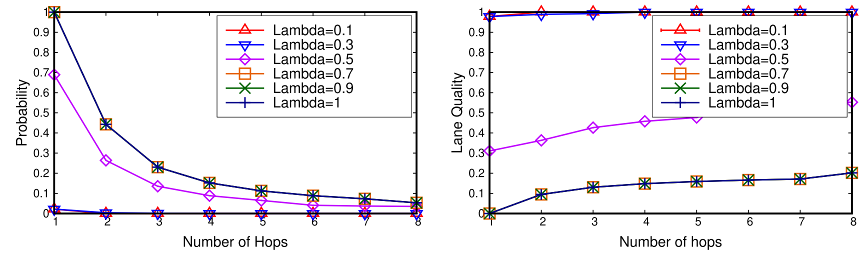
V. Performance Evaluation and Simulation Results

This section evaluates the performance of CNP risk assessment mechanism. It compares the performance of CNP with other communication mechanisms in terms of communication overhead. It evaluates the performance of CNP safety mechanism in terms of collision risk reductions. It assesses the collision mitigation by the equivalent energy speed and the number of colliding vehicles. We carried a simulation implementation to evaluate CNP performance.

A. Simulation Setup

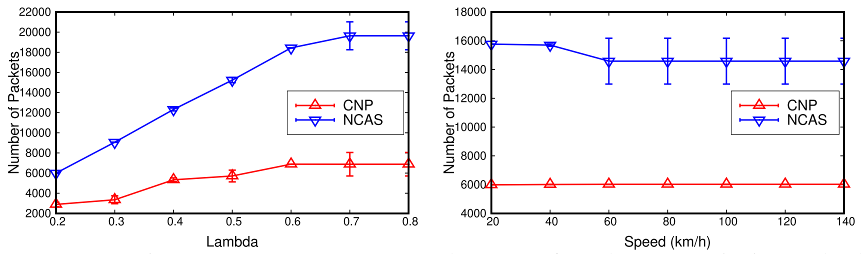
To be able to evaluate the correctness and efficiency of this scheme, we conducted a simulation with the simulation of urban mobility (SUMO) [28] and OMNeT++ simulation framework [29]. We made an urban mobility simulation where multiple vehicles are traversing in a road and exchange the mobility information for safety purpose. With OMNeT++, we simulated CNP centralized network communication. Vehicles exchange the Emergency Context Messages (ECM) as WAVE Short Messages (WSM) within an IEEE.11-OCB enabled network simulation environment. Table I lists the simulation configuration parameters.

To allow SUMO to meet the demands of the CNP mechanism, we modified the $SL2015$ [30] lane changing mechanism to comply with the coordinated maneuver mechanism. We extended Krauss' car following model and SUMO lane changing strategy that enables both the collisions to occur



(a) Lane collision probability (b) Lane quality

Fig. 7. Impact of the number of considered hops on the lane quality.



(a) Impact of λ on communication overhead. (b) Impact of speed on communication overhead.

Fig. 8. Impact of CNP on communication overhead.

when not avoided. For collision avoidance, an increased lateral resolution for sublanes in SUMO allows realistic lane changes of vehicles. Through a communication strategy in our proposal, vehicles get informed of the existence of obstacles and can preemptively maneuver prior to reaching a high collision risk.

B. Performance Parameters and Metrics

The evaluation of this mechanism is based on the following evaluation settings.

- **Parameters:** The parameters for evaluation are: the impact of *(i) vehicle injection rate (λ), (ii) maximum driving speed, and (iii) acceleration*.
- **Metrics:** The metrics for evaluation are: the communication overhead to measure the communication performance, the collision probability to measure collision risk, the number of collisions, and the collision equivalent energy speed as metrics for collision strengths.
- **Baselines:** We compare CNP with legacy situational awareness, which are sensor-based approach (e.g., LIDAR), a collision avoidance (CA) based [21], and a networked approach (e.g., NCAS [14]). Unlike CNP and NCAS, the sensor detects the situation only in the Line-of-collision (LOC) of vehicles.

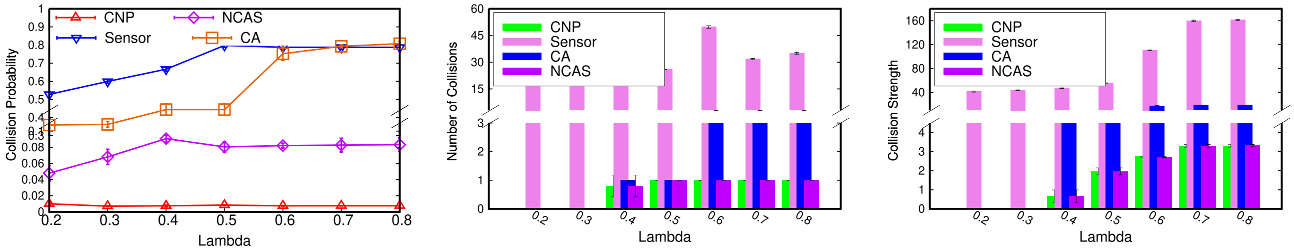
To test the performance of the CNP, we use a road segment with three lanes. Our simulation results use a 95% confidence interval.

C. Simulation Results

1) Lane Quality: This section investigates the safe lane quality (mentioned as lane quality) of the CNP, which is defined by Definition 1, by measuring the impact of the number of hops that were taken into account in the CNP's risk assessment calculation on the lane quality. To determine the quality of the lane driving, we evaluate the impact of the hop number on collision probability considering the different number of hops in the lane. First, consider only vehicles within the LOC of n_1^E, and then consider two hops away from n_1^E, and then three hops away, and so on.

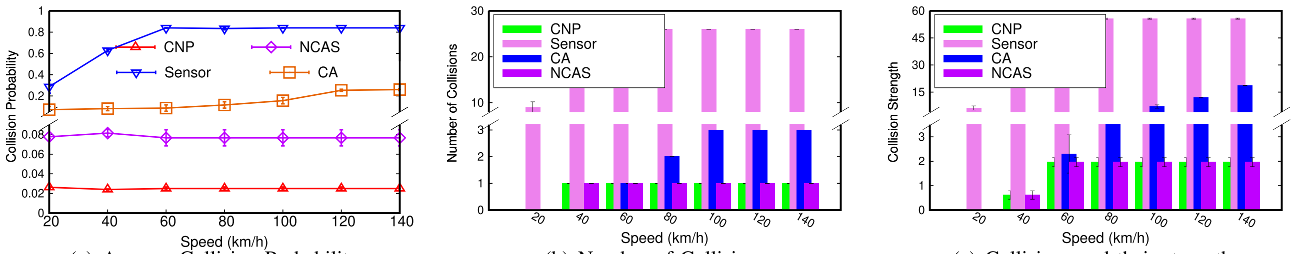
Fig. 7(a) shows that for both the vehicle injection rates, the risk of collision is high if the CNP assesses the risk only to its neighbors. The greater the number of vehicles in the lane that are considered by the risk assessment is, the lower the risk of collision is. Similarly, as shown in Fig. 7(b), considering a small number of vehicles in the CNP risk assessment will result in poor safe lane quality. Higher injection rates (e.g., $\lambda = 1$) result in poorer safe lane quality as road congestion increases. Assessing up to 3 hops can ensure adequate safe lane quality and less complex calculations. This gives a collision probability equivalent to 0.15 for $\lambda = 1$ and one equivalent to 0.11 for $\lambda = 0.5$. Their safe lane qualities are 0.13 and 0.5, respectively, which is safe enough to limit the risk of a chain of collisions.

2) Communication Control Overhead: Both CNP and NCAS are communication-based mechanisms to avoid crashes in vehicular networks. Unlike NCAS, CNP uses a coordinated communication protocol and CH is the orchestrator of the remaining CMs' maneuvers. Fig. 8(a) shows the evaluation of communication overhead in a vehicular networks wherein vehicles drive at $80km/h$ and are injected at injection rate $\lambda \in [0.2\,0.8]$. The results show that CNP reduces the communication overhead caused by NCAS from 15% to 60%. Fig. 8(b) shows an overhead comparison figure where vehicles drive with maximum speeds varying from 20 to $140km/h$ while maintaining an injection rate of 0.6. The results shows that CNP reduces the overhead caused by the NCAS communication control by up to 60%.



(a) Average Collision Probability (b) Number of Collisions (c) Collisions and their strengths

Fig. 9. Impact of injection rate (λ).



(a) Average Collision Probability (b) Number of Collisions (c) Collisions and their strengths

Fig. 10. Impact of speed.

3) Impact of the Vehicles Injection Rate λ: This section investigates the impact of vehicle injection rate λ on the overall CNP performance compared with the baselines. It is seen that CNP reduces the risks of vehicles colliding with an obstacle. Fig. 9(a) shows that over time, on average, the risk of colliding either with obstacles or other vehicles in CNP is always the smallest. For unavoidable crashes, Fig. 9(b) shows that CNP has the smallest number of collisions at all injection rates. At higher injection rates, the number of sensor-based collisions in the presence of obstacles will be greater than the collisions found with both communication mechanisms (i.e., CNP and NCAS). Another factor that measures the nature of collisions is the energy transfer between collision nodes (including vehicles and obstacles), which is measured by EES.

Fig. 9(c) shows that in most cases, the cumulative energy when CNP is applied is lower than that found only by relying on sensor-based approach (Sensor) and equivalent to the benefits of NCAS. The smaller the EES, the lighter the collision which reduces the accident casualties. As shown in Fig. 9, the overall results indicate that CNP outperforms the sensor-based approach on all levels of tested injection rates.

4) Impact of Speed: To investigate the impact of speed, we set different speed limits in the range from $20km/h$ to $140km/h$ and fixed the injection rate to 0.6 and tested the behavior of CNP in comparison with the baselines. Fig. 10 shows the evaluation of collision risks when there is an obstacle on the road. For all speeds, the CNP outperforms the sensor and NCAS approaches in terms of the three metrics such as collision probability, the number of collisions, and collision strength. The collision probability with CNP is 5% less than NCAS while it grows to 85% of sensor-based approach as depicted by Fig. 10(a). On average, CNP reduces 5% of the chances of collisions of NCAS, and 80% of those of the sensor-based risk assessment.

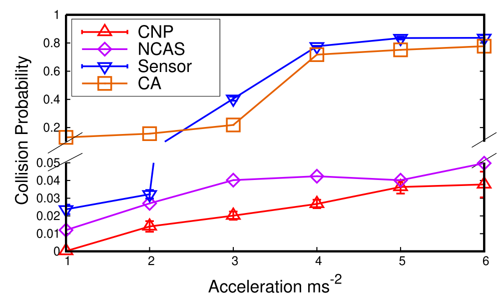


Fig. 11. Impact of acceleration.

Fig. 10(b) shows that CNP outperforms the sensor-based approach in the reduction of the number of possible collisions. At all speeds, CNP has fewer or the same number of vehicle collisions compared with the NCAS's, and much fewer than the sensor-based approach. For speeds greater than $60km/h$, the number of possible collisions when using the sensor risk assessment is much higher than those of the CNP and NCAS, showing that network-based risk assessments have better performance. CNP has the lightest collisions compared to the baseline as shown in Fig 10(c).

5) Impact of Acceleration: We investigated the impact of acceleration/deceleration by testing accelerations/decelerations that vary from $|1|m/s^2$ to $|6|m/s^2$ in Table I. The results in Fig. 11 show that the lower acceleration leads to the higher safety. That is, the safety weakens with the increase of acceleration. For all the acceleration scenarios, CNP outperforms other the compared risk assessment methods.

D. Discussion

The communication protocol in CNP was simulated according to the 802.11p standard. This protocol needs the vehicles to respond to the driving environments in a timely manner and to handle complex driving functions. For this to be possible, a powerful computational system capacity which enables vehicles to collaborate with each other is required.

The standardization of 802.11p and 3GPP have substantially improved the robustness and reliability of vehicular networks, thus it allows them to communicate with each other without an infrastructure. However, a limited processing speed would lead to inaccurate decisions. Intel Corp. estimates that approximately 1 GB of data needs to be processed each second in the car for collaborative driving [31]. Vehicles with graphics processing units (GPUs) for computation acceleration can handle such cognitive processing loads efficiently.

VI. Conclusion

This paper introduced a context-aware navigation protocol (called CNP) to enhance the driving safety of vehicles moving in urban roads. The CNP's collision avoidance feature allows vehicles to drive safely in the presence of obstacles or accidents in the road by perceiving the situation and determining safe paths to follow. If a collision occurs, collision mitigation minimizes any damage. The simulation results have shown that CNP outperforms the sensor-based approach in reducing the risks of collisions, the number of collisions, and the strength of collisions.

As future work, we will enhance our collision probability computation, considering the reaction time of a vehicle. Also, we will implement and test this CNP protocol on real cars to improve its accuracy and usability for safe driving. We will also test the impact of the CNP on the overall trajectory performance of the driving vehicles as another way to test and improve the navigation efficiency.

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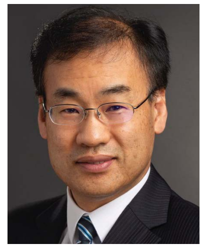
Bien Aime Mugabarigira (Student Member, IEEE) received the B.S. degree from the Department of Computer Sciences, National University of Rwanda, in 2012. He is currently pursuing the Ph.D. degree with the Department of Electrical and Computer Engineering, Sungkyunkwan University, South Korea. His research interests include intelligent transportation systems, wireless networks, and VANET.

Yiwen (Chris) Shen (Member, IEEE) received the B.S. degree from the Department of Communication Engineering, North University of China, in 2009, the M.S. degree from the Department of Mechatronics Engineering, North University of China, in 2013, and the Ph.D. degree from the Department of Electrical and Computer Engineering, Sungkyunkwan University, South Korea. His research interests include intelligent transportation systems, wireless networks, the IoT, and indoor localization.

Jaehoon (Paul) Jeong (Member, IEEE) received the B.S. degree from the Department of Information Engineering, Sungkyunkwan University, in 1999, the M.S. degree from the School of Computer Science and Engineering, Seoul National University, in 2001, and the Ph.D. degree from the Department of Computer Science and Engineering, University of Minnesota, in 2009. He is currently an Associate Professor with the Department of Computer Science and Engineering, Sungkyunkwan University. His research interests include vehicular networks and network security.



Tae (Tom) Oh (Senior Member, IEEE) received the B.S. degree in electrical engineering from Texas Tech University, Lubbock, TX, USA, in 1991, and the M.S. and Ph.D. degrees in electrical engineering from Southern Methodist University, Dallas, TX, USA, in 1995 and 2001, respectively, while working for telecommunication and defense companies. He is currently a Professor with the School of Information, Rochester Institute of Technology. His research interests include vehicular networks, the IoT and mobile security, and assistive technology.

Han-You Jeong (Member, IEEE) received the B.S., M.S., and Ph.D. degrees in electrical engineering and computer science from Seoul National University, Seoul, South Korea, in 1998, 2000, and 2005, respectively. In 2008, he joined the Digital Technology Center, University of Minnesota, Minneapolis, MN, USA, as a Post-Doctoral Research Fellow. He is currently a Professor with the School of Electrical and Computer Engineering, Pusan National University. His research interests include cooperative driver assistance systems, cooperative awareness in vehicular networks, and vehicular localization.