Design of V2X-Based Vehicular Contents Centric Networks for Autonomous Driving

Sanghoon Lee, Younghwa Jung, Young-Hoon Park, and Seong-Woo Kim, *Member, IEEE*

***Abstract*— Recent technical innovation has driven the evolution of autonomous vehicles. To improve safety as well as on-road vehicular experience, vehicles should be connected with each other or to vehicular networks. Some specification groups, e.g., IEEE and 3GPP, have studied and released vehicular communication requirements and architecture. IEEE's Wireless Access in Vehicular Environment focuses on dedicated and short-range communication, while 3GPP's New Radio V2X supports not only sidelink but also uplink communication. The 3GPP Release 16, which supports 5G New Radio, offers evolved functionalities such as network slice, Network Function Virtualization, and Software-Defined Networking. In this paper, we define and design a vehicular network architecture compliant with 5G core networks to enable and support autonomous driving. As a validation example, a high-definition map needs to contain the context of trajectory for localization and planning of autonomous driving vehicles. We also propose new methods by which autonomous vehicles can push and pull map content efficiently, without causing bottlenecks on the network core. We evaluate the performance of the proposed method via network simulations and our autonomous driving vehicle on the road. Experimental results indicate that the proposed method improves the performance of vehicular content delivery in real-world road environments.**

***Index Terms*— Autonomous driving, cooperative perception, C-V2X, HD map, vehicular content centric networks.**

I. Introduction

The evolution of technologies such as AI, telecommunication, and big data affects not only the IT industry but also traditional machinery and process industries such as automobiles, which can apply these innovations in autonomous driving. The Society of Automotive Engineers (SAE) International defined six levels of automated driving [1]. As per SAE automation levels, a Level 5 Autonomous Vehicle (AV) should be able to perceive a road environment and maneuver itself independently. A crucial prerequisite for a higher level of automation is the ability to guarantee the safety of the vehicle and its passengers by precisely predicting risks and devising a driving plan that eliminates the possibility of accidents. Contemporary self-driving platforms focus on realizing perception abilities comparable to those of human drivers.

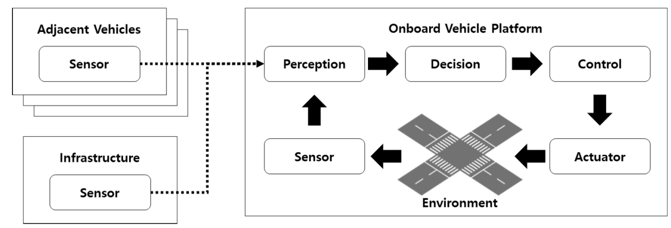

Fig. 1. Architecture of a connected autonomous vehicle platform.

A functional architecture for autonomous driving consists of modules focused on perception, decision, control, and manipulation [2]. For high-level automation, a sensor-equipped vehicle must detect the surroundings in detail and perform instantaneous driving decision planning and control. Long-range sensors can be used to extend AV's perception range. However, AVs are unable to perceive beyond the Non-Line of Sight (NLOS) of the sensors embedded in it [3].

In order to overcome this limitation, AVs could be connected to each other or to a vehicular network in order to share sensing data, as shown in Table I. The concept of Connected Autonomous Vehicle (CAV) over Vehicle-to-Everything (V2X) communication for complementing the perception and awareness of AVs has been discussed by the academic community, standardization groups, and telecommunication operators, all of whom have contributed to vehicular communications [4]. The connectivity of vehicles, infrastructure, and pedestrians is expected to improve safety [5] as well as traffic efficiency [6].

The characteristics of the vehicular contents differ from existing client-server communication models. Figure 1 illustrates that the CAV merges its own collected sensor data with information received from adjacent vehicles, infrastructure, and pedestrians [7], where the form of post-processed data can be raw point clouds [8], extracted features [9], and multimodal fusion [3]. The collected data is used for localization, object detection [10], intention-awareness [11] and safe driving control [5] of autonomous driving as well as

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TABLE I
VEHICULAR COMMUNICATIONS AND NETWORKS FOR SPATIAL AND SITUATIONAL AWARENESS

	Non-Cellular		Cellular V2X	
	V2V	V2I	Core	Edge
Driving Assistance	[3], [15]	[16], [17]	[18], [19]	[12]
Autonomous Driving	[5], [8]	[10], [20]	[21], [22]	Proposal

driving assistance. Cooperative perception has been a major focus of V2X applications [12].

Since the first V2X standard IEEE 802.11p was released in 2010, subsequent research has helped the architecture, specifications, protocols, and applications for vehicular communication to evolve considerably. IEEE Wireless Access Vehicular Environments (WAVE) and ETSI ITS-G5 are IEEE 802.11p-based Dedicated Short-Range Communications (DSRC), which disseminate content within the range as a wireless LAN. WAVE adopted SAE J2735 message protocols for cooperative awareness, e.g., Basic Safety Message (BSM). WAVE utilizes broadcast transmission via a dedicated control channel, which improves the delay performance as compared to unicast. However, as the number of participants and the content increases, the probability of transmission success decreases owing to congestion [13]. Consequently, it is required to identify important vehicular content such as accident warning and distribute it over multiple channels [14].

Perception information and content in networks is used to determine precise localization and mapping, which are crucial for autonomous driving [23]. An AV estimates the precise position and orientation by comparing the sensor data and the built-in geographical content, e.g., High-Definition (HD) Map [24]. However, it is impossible to carry complete geographical and updated data within a single vehicle because on-board storage is a limited computing resource. Offloading HD maps to the remote cloud server could be an alternative [25], but this causes a serious bottleneck effect for time-critical autonomous driving when multiple AVs request data simultaneously, as demonstrated in our experiments. For this reason, we consider caching and distribution on the edge side in order to mitigate those effects. In this paper, we propose a content centric edge networks architecture for autonomous driving in the context of cooperative perception, where HD map acquisition corresponds to content delivery.

The contributions of this paper can be summarized as follows:

- We propose a content centric edge network for efficient caching and data distribution on the edge side.
- The proposed method maximizes the efficiency of edge utilization in vehicular content delivery, which meets the real-time constraint of autonomous vehicles.
- We compare the proposed method to several baselines; our method shows the best performance in a simulated and real environment.

The remainder of the paper is organized as follows. Section II describes the literature on cooperative perception algorithms over V2X, Vehicular Content-Centric Networks (VCCN), and caching on the vehicular edge node. Section III

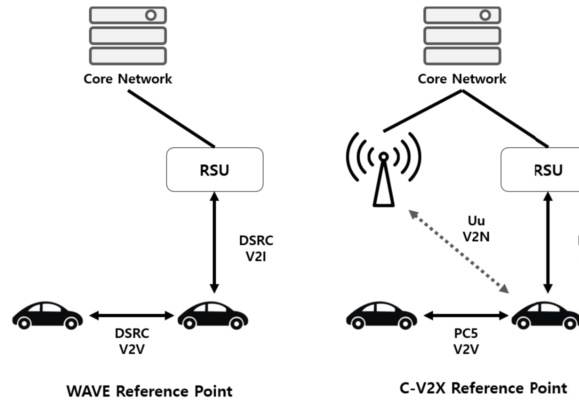


Fig. 2. Reference points of WAVE and C-V2X.

describes the 3GPP-enhanced C-V2X architecture and defines the roles and functions of each network entity. Based on C-V2X architecture, a methodology involving cooperative perception via multiple channels and offloading geometric information on the edge node are proposed. In Section IV, we evaluate the performance of the proposed algorithm using simulations and experiments. In Section V, we conclude our works and suggest ways to overcome further challenges.

II. RELATED WORKS

In this chapter, we will review V2X, geometric content, and content delivery networks, which are the key elements of VCCNs for autonomous driving.

A. V2X Standardization

1) IEEE Wave: IEEE WAVE was introduced to support V2V and V2I for traffic information broadcast. IEEE released IEEE 802.11p originating from 802.11a in 2010, which reduced the channel bandwidth to 10 MHz and utilized the frequency spectrum around 5.9 GHz [26]. WAVE adopts IEEE 802.11p, which defines the specification of PHY and MAC layers, and the 1609 series for LLC sublayer, WAVE short message protocol (WSMP), and security.

For V2X services, SAE J2735 describes 17 protocols for messages, data frame format, and application architecture, and SAE J2945.1 defines the minimal requirements. Seventeen messages include the Basic Safety Message (BSM) that broadcasts vehicular positions, events and Single Phase and Timing (SPaT) message that notifies the cycle information of traffic lights.

WAVE can deploy a distributed and decentralized network regardless of core network controls. However, IEEE 802.11p has limitations, such as a hidden node problem. WAVE includes contention-window techniques and adaptive message frequency techniques to decrease the congestion, but these cannot be applied in high-density networks. IEEE 802.11p is not suitable for high-data ultra-low latency applications as it has a large communication overhead that consumes bandwidth and increases latency in error retransmission. The NLOS of radio propagation and dynamic conditions of V2X always interrupt the connection [27]. For this reason, Cellular-V2X has been considered as an alternative [22].

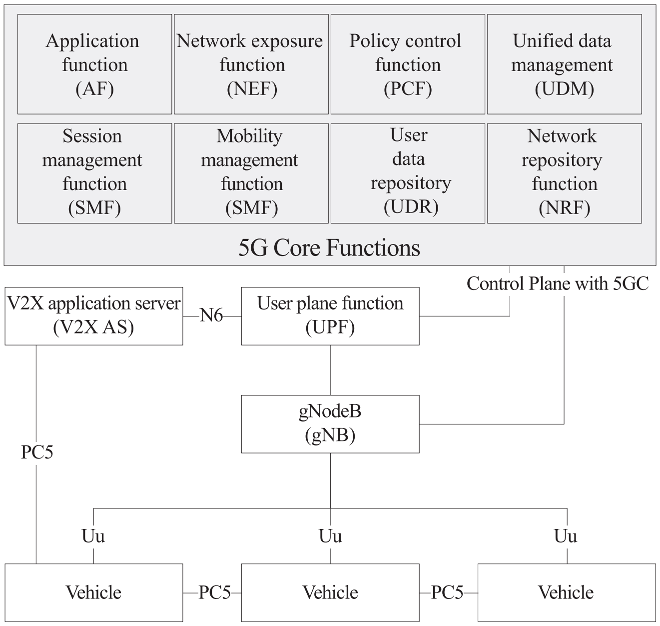


Fig. 3. Architecture of NR V2X.

2) 3GPP C-V2X: The 3rd Generation Partnership Project (3GPP) is an alliance of telecommunications standard development organizations, which covers cellular telecommunications technologies including radio access, core network, and service capabilities. In addition to DSRC, a cellular vehicle network can be an alternative, thereby solving a communication coverage problem and transmitting more data [28]. 3GPP initiated the V2X working group and released the first LTE-based V2X specifications, Release 14, in 2017. Cellular V2X (C-V2X) can utilize the uplink communication offered by Bases Station (BSs) and Device-to-Device (D2D), like DSRC. A feasible network scheme supports various vehicular scenarios including V2V, V2I, and V2P, as shown in Figure 2. 3GPP defines V2V interface as sidelink telecommunication.

Owing to the emergence of 5G NR (New Radio), 3GPP has also evolved V2X requirements and schemes based on new keywords, such as millimeter wave, beam forming, adaptive numerology, and network slice. Release 16, approved in 2018, had enhanced V2X use cases, e.g., platooning, extended sensor, remote driving, and advanced driving. The main items include sidelink design, Uu link enhancement to support enhanced V2X use cases, Uu link-based sidelink resource allocation/configuration, QoS management, and coexistence.

Initial synchronization can happen by receiving a signal from a base station (gNB or eNB). However, when the vehicle terminal is outside the coverage area, it is possible to obtain synchronization by receiving a global navigation satellite system (GNSS) signal or a Sidelink Synchronization Signal from an adjacent terminal.

In case of allocation, terminals and cell can choose the Sidelink mode. In Mode 1, a vehicle (User Equipment) allocates resources of adjacent vehicles. In mode 2, the vehicle can sense through adjacent vehicles. Modes 3 and 4 support direct V2V communications but differ on how radio resources are allocated. Resources are allocated by the cellular network under Mode 3. Mode 4 does not require cellular coverage; vehicles autonomously select their radio resources using a distributed scheduling scheme supported by congestion control mechanisms [29].

TABLE II
COMPARISON OF GEOSPATIAL DATABASE

Database	Supported Geometry Objects	Supported Spatial Indexes	Data Format
MongoDB	Point, LineString, Polygon, MultiPoint, MultiLineString, MultiPolygon, GeometryCollection	2dsphere index, 2d index based on geohash	GeoJSON
Couchbase	Point, LineString, Polygon, MultiPoint, MultiLineString, MultiPolygon, GeometryCollection	R-Tree, designed by users	GeoJSON
Cassandra	Point, LineString, Polygon	Lucene index	WKT
Redis	Point	geohash	GeoJSON

Compared with the LTE core network, the 5G Core showed major differences in structural and procedural terms [30], where new terminologies of network entities were introduced, Control Plane and User Plane were separated, and network functions were modularized.

As the 5G core architecture was renewed, V2X specifications were also changed. TS 23.287 defined NR V2X reference points and architecture, as shown in Figure 3. A vehicle as User Equipment (UE) supports up/downlink via the Uu reference point and sidelink via the PC5 reference point. The V2X Application Server provides vehicular services, such as accident and congestion warning, platoon driving, and HD Map acquisition, where V2X AS controls UE requests and prioritizes transactions. Among the potential scenarios, event detection via cooperative perception in C-V2X has been proposed [12].

B. Geographic Contents

Geometries in a map for navigation can be described by the group of points, line strings, and polygons. GeoJSON is an open standard format designed to systematically express terrain based on location information by IETF RFC 7946 [31]. GeoJSON is compatible with GPX, which makes it possible to compress the polyline and load the application program with light-weight data. As geographic content becomes more complex and larger in size, efficient database management is required. A DBMS specialized for geographic content and rapid querying is proposed. Table II summarizes the features of a NoSQL database supporting geospatial functions [32].

ETSI defined the interfaces and architecture of Local Dynamic Maps [33]. As shown in Figure 4, the HD map has a layered structure. Layer 1 represents a base map such as geometric information. Layer 2 shows the layout of roadside infrastructure, e.g., traffic lights, road signs, and lane markings. Layer 3 represents time-variant information such as traffic congestion and signal phase of traffic light. Layer 4 shows dynamic information where vehicles and pedestrians move, which can be shared through V2V direct communications.

With GNSS, such as GPS, AVs can estimate their positions. However, it needs to localize itself more accurately

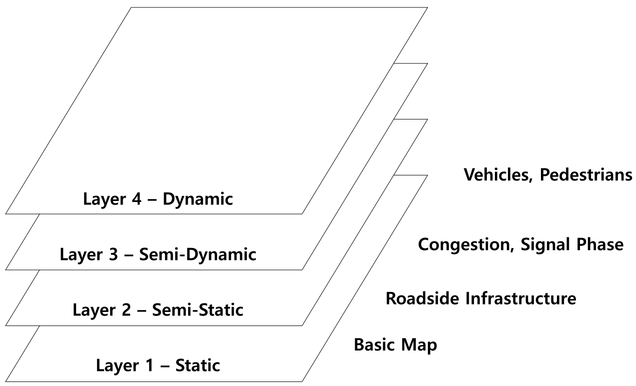


Fig. 4. HD Map layers.

in the real-world environment. A feature map for vehicle localization, which has high precision at centimeter-level, is essential for autonomous driving [34]. A navigation map contains only basic information, link, and node information of roads. An HD Map typically contains information on traffic lights, signs, curbs, road marks, and various structures as well as information on each lane level such as the road center line and boundary line in a 3D digital format. This will be explained in Section IV-C. By feature mapping between map elements and detected objects, autonomous vehicles can calculate centimeter-accurate positions and dynamics.

During the localization process, an autonomous vehicle integrates GNSS, LiDAR, Radar, and Camera [35]. Integrating more and higher sensor equipment reduces the error caused by device specification and environmental noise but increases costs and resource usage. Utilizing an HD map can reduce the diversity of on-board equipment and ensure better performance. Sven *et al.* introduced the particle filter-based localization algorithm utilizing HD maps, GNSS, and odometry [24]. Hao *et al.* estimated vehicular position using only HD maps, monocular vision, and GNSS [33]. The road signs perception information by the LiDAR scanner is matched with features on HD map so that the vehicular system can infer the position accurately [36], [37]. Chen *et al.* presented 3D point cloud-based cooperative perception for autonomous driving using the KITTI dataset [8], [9].

C. Vehicular Contents Centric Network

Content-Centric Network (CCN) and Information-Centric network (ICN) are emerging as next-generation network architecture, in contrast to Host-Centric Network. A Host-Centric Network consists of clients and servers, where all network entities route and forward data by resolving the host address. By contrast, ICN reverses an address-centric approach into a content-centric one [38], [39]. Similarly, CCN is based on the contents of data instead of the host address, which designs elements of the network that utilize the identifiers or names of contents instead of the address of the host [40].

In CCN networks, a content consuming node asks for specific content by sending an Interest Packet via the network. A receiver that possesses the relevant content responds by sending a Data Packet. The Interest Packet includes a detailed description of content name, preference in case multiple types

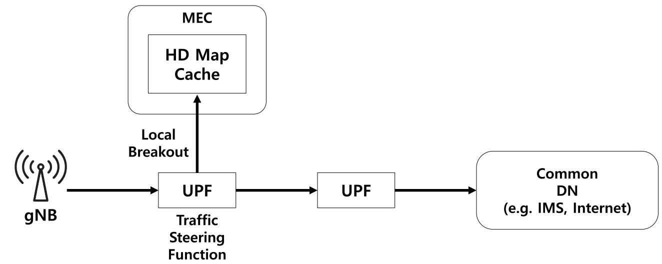


Fig. 5. Local traffic steering at edge side.

of content match, and items for security. The Data Packet contains signed information of public key digest, time stamps, and encryption description.

The CCN forwarding mechanism has three main components: Content Store (CS), Pending Interest Table (PIT), and Forwarding Information Base (FIB). CCN supports multiple faces connected with other interfaces. Similarly, with the buffer memory of a router, CS stores data content and lists and exchanges caches based on the Least Recently Used (LRU) or Least Frequently Used (LFU) policy.

Recently, studies on the feasibility of applying CCN concept to vehicular networks have been conducted. CCN is advantageous in dynamic and mobile environments such as for vehicular communications [41]. The CCN architecture applied to V2X is named Vehicular Content-Centric Network (VCCN), which has certain specific characteristics e.g., content naming, name resolution, and assigning roles of CCN nodes like CS, FIB, and PIT [42].

Note that the non-deterministic delay in vehicular content delivery is safety-critical. Hence, several broadcast mechanisms were proposed to deliver rapidly emergency warning packet in driving environments [43]. For minimizing delivery delay, VCCN usually leverages a caching algorithm that considers popularity, vehicle mobility, and cache capacity in edge nodes [44]. Road Side Unit (RSU) can play a role not only as a base station [7], [20], [45] but also as caching storage for vehicles. In vehicular content delivery, interesting content depends on the given positions of consumers, so content returned by the nearest provider can reduce the number of resources needed [46]. Vehicles can be consumers as well as providers of information. With sidelink communication, vehicles can share content with adjacent consumers and manage their own onboard caches. Mobile vehicular caches can improve the spatial and situational awareness for safe and efficient driving [47]. In this paper, we focus on vehicular content centric networks with time-critical caching for autonomous driving.

D. Caching Method

A cache algorithm is a conventional concept that has been studied for a long time in computer science, where they have researched to provide immediate accessibility in processing logic between processor and memory. A fundamental operation is cache replacement, which erases redundancy and writes a candidate to be read by the processor. Classical methods, e.g., First In, First Out (FIFO), Last In, First Out (LIFO), Least Recently Used (LRU), and Least Frequently Used (LFU) are

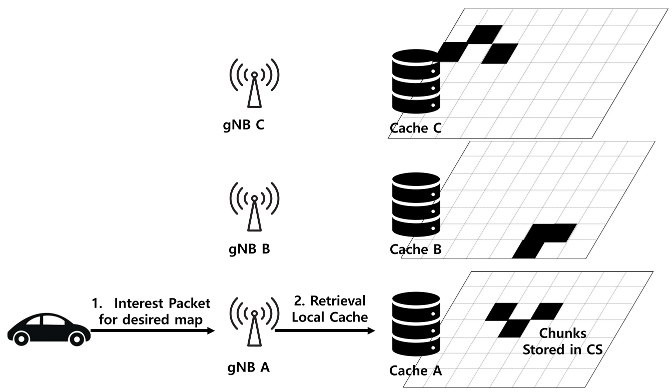


Fig. 6. Requesting chunks procedure.

utilized to design a processor and web server architecture [48]. FIFO evicts the old cache first and then adds a new one, whereas LIFO clears recently used data. FIFO and LIFO leverage stack architecture of memory, so that they operate immediately. However, LRU and LFU operate according to statistics, where LRU deletes the cache that has been unused for the longest time. By contrast, LFU places only frequent data and removes rarely used data.

Unlike cache replacement in a conventional domain, vehicular content, such as static HD map and dynamic road environment perception, should be handled with mobility awareness because consumers and producers of vehicular contents are not spatially fixed but continuously moving. In [49], three algorithms were proposed to alleviate the impact of the mobility of vehicles on caching performance by distributing large-size content at the edge servers. The first one exploits exhaustive searching and can achieve the best performance in downloading time. However, it has the highest computation complexity. The second one allocates the most popular contents in all RSUs and does substitution repeatedly. The last one with greedy strategy clears the RSUs at first and then makes the currently best choice each time. Hence, it has the lowest complexity.

With the advancement of deep neural networks (DNNs), a DNNs-based caching algorithm was proposed to reduce the delivery delay of entertainment content for intelligent vehicles [50]. Additionally, in [51], a caching strategy is proposed to minimize the caching server delay by predicting the mobility of vehicles, where the mobility of vehicle is predicted by a long short-term memory (LSTM) network-based architecture.

III. System Modeling

In this section, we will define the roles and procedures of each network entity for HD map cache and acquisition according to the NR V2X specification introduced in Sec. II-A.

A. NR-V2X Architecture Analysis

5GC in Release 16 supports vertical service networks and edge computing. Profiles of vehicles should be provisioned and registered in Unified Data Management (UDM) before attaching to networks. UDM manages a V2X service provision profile. Configurations, such as radio parameters, QoS, and Public Land Mobile Network (PLMN) properties stored in User Data Repository (UDR) are forwarded to Application Servers, gNodeB (gNB), and vehicles over a control plane via Policy Control Function (PCF), referred to Figure 3.

On the edge side, contents stream from UEs branches into Local Data Network and Core Data Network according to the ETSI Mobile Edge Computing (MEC) specification [52]. As shown in Figure 5, local User Plane Function (UPF) supporting MEC steers the data stream as per HD map interest and interest packets are processed at the edge server on MEC. Local steering reduces the number of nodes between map consumer and provider, which can prevent bottlenecks at the core side. Cache servers supporting NR V2X Uu and PC5 sidelink are responsible for the specific geographic region allocated by V2X AS. Each cache server consists of CS, FIB, and PIT, and maintains content based on the caching policy.

In the proposed system, the performance of wireless communication can be determined by Packet Error Rate (PER) and End-to-End delay time. Let δ be the PER interval that is divided into w sub-window intervals, normally set to one second. $\delta = n \cdot w$, where n is normally set to five seconds PER value. At the end of each sub-window interval w, the PER is calculated at the end of each δ for the last n sub-windows, which can be formulated as

$$PER = \frac{\text{missed number of packets}}{\text{total number of packets}}. \tag{1}$$

According to [53], PER can be approximated by an exponential function as Equation (2), where γ denotes SNRs and m denotes MCS index, which can be formulated as follows:

$$PER^{(m)}(\gamma) = \begin{cases} 1 & \text{for } \gamma < \gamma^{(m)} \\ \exp(-\alpha^{(m)}(\gamma - \gamma^{(m)})) & \text{for } \gamma \geq \gamma^{(m)}, \end{cases} \tag{2}$$

where $\alpha^{(m)}$ and $\gamma^{(m)}$ are an exponential decay ratio and SNR computed by simulations at each MCS index m, respectively. The performance of this proposal is evaluated with Equations (1) and (2) in Section IV-C.

B. Caching Strategy for HD Map Acquisition

A global map is divided into several chunks for edge caching. Cache servers are located on the edge side of the vehicular network. Initialized cache servers store only the nearest chunks from a responsible location. Assuming that a vehicle has set up path plans, it is necessary to fetch maps of the trajectory. If a vehicle does not possess maps on the desired trajectory in the vehicular buffer, it will try to request maps from the edge network. The cache server stores chunks of the map for the relevant region as per the cache initialization policy, as shown in Figure 6. If the cache server stores the desired chunks, it will respond to the interest packet and transmit content to the vehicle. If not, a local cache will forward the interest packet to the upper-level server on the core of network or an adjacent cache server and record on FIB and PIT.

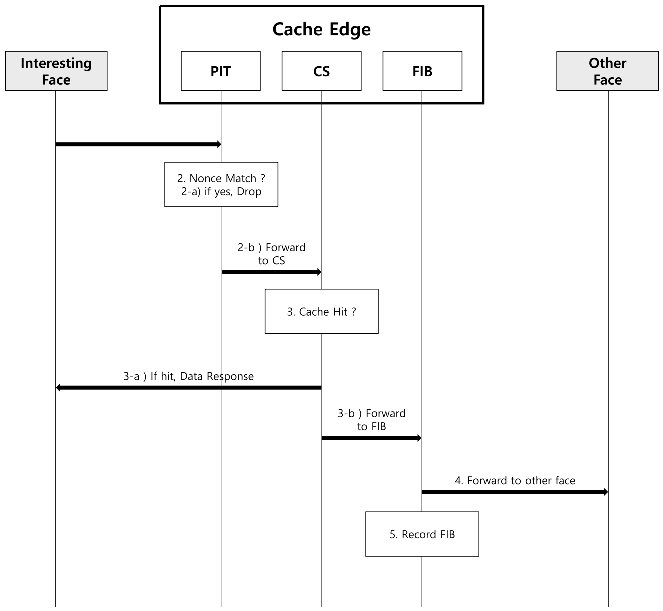


Fig. 7. On receipt of interest from requester, cache server checks if PIT has a pending interest on desired nonce.

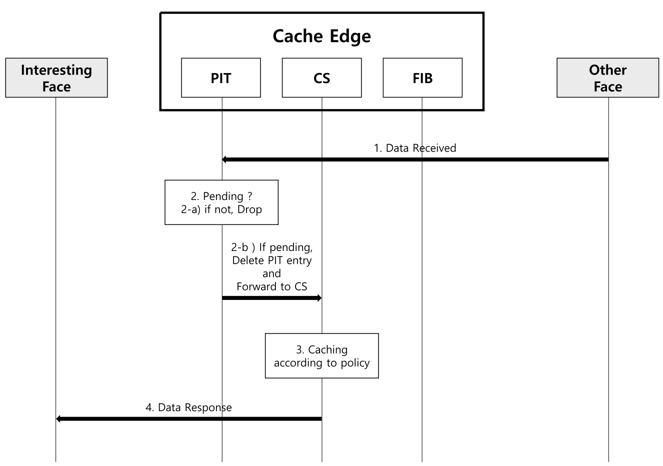


Fig. 8. On receipt of data from face, PIT checks the pending records and forwards data.

First, the cache server checks if PIT has a pending interest on desired nonce, as shown in Figure 7. In the case of PIT match, PIT discards the interest; otherwise, PIT forwards the interest to CS. In this case, it is possible to reduce delay in responding to the consumer. CS searches matched chunks in the storage. If cache hits, CS will answer to the interesting face. If cache misses, CS will relay the interest to the other face via FIB. FIB records the transaction with the other face.

When data chunks arrive at the face of cache server, PIT checks the pending records, as shown in Figure 8. PIT searches the pending records with respect to the received data. If a record matches, PIT will forward to CS, and CS determines whether or not to store the data on the server. If not, PIT discards the data. As described in the procedures above, a caching policy affects an immediate delivery of interest and response messages, which can predict the chunks to be requested because it has limited space to store data. Therefore, the cache server should manage requests from the consumer and orchestrate chunks in storage effectively. The main objective of the cache strategy is to increase the probability of hitting its caches without fetching the chunks from the origin content server.

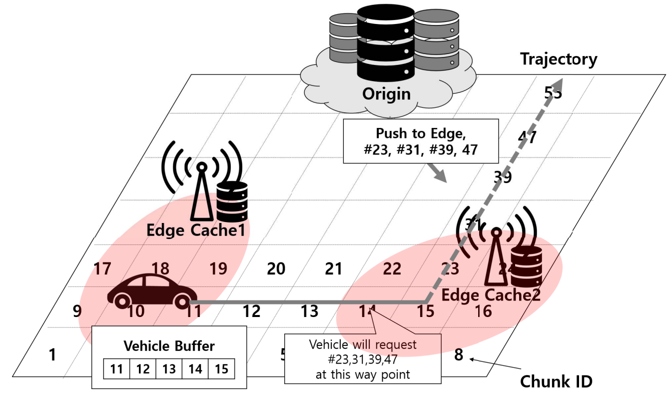


Fig. 9. Overview of vehicular content delivery.

For the goal, we assume a road environment with wireless stations that are connected to vehicles and store vehicular content at the edge. A vehicle has its own buffer to load the HD map chunks, and according to buffer policy, will request other chunks on its trajectory in the future. In Figure 9, Edge 1 is responsible for the vehicle content at the initial time, although this will be disconnected soon. The vehicle will move to an area regarding chunk ID 14 and will fetch the chunks 23, 31, 39, 47, and 55. If Edge 2 stocks up those chunks, the vehicle will hit the caches and load its buffer in a shorter time. Most vehicles have a trajectory plan to the destination and can estimate the approximate direction and position in the near future [54]. Therefore, we propose the method to reserve the future chunks with its trajectory information.

Specifically, trajectory consists of n chunks corresponding to way points. t_n represents the time to reach at the way point of n-th chunk. The probability to go off the scheduled path plan will increase over time. Therefore, the reservation weight value decreases with time as described in Equation (3). We assume that k vehicles subscribe to the HD map service.

$$\vec{w_{n,i}} = \zeta \cdot \exp\left(-\beta \cdot t_n\right) \cdot \vec{v},\ |\vec{v}| = 1, \tag{3}$$

where ζ and β are hyper-parameters. $\vec{v}$ is the i-th vehicle's direction vector at the center point of the chunk, which can be calculated based on trajectory direction. This assumption will be validated through experiments in Sec. IV. The vehicle reports reservation weight value corresponding to each chunk except for chunks already loaded in the buffer to V2X Application server. The V2X application server merges weight values from vehicles and calculates total weight value of the chunk. Therefore, we can derive the total weight vector of each chunk as follows:

$$\vec{w_n} = \frac{1}{k}\sum_{i}^{k} \vec{w_{n,i}} = |\vec{w_n}| \cdot (-\vec{r}), \tag{4}$$

where $\vec{r}$ represents the request possibility vector and its direction is the opposite of that of $\vec{w_n}$. The probability of an interest occurring in the direction indicated by $\vec{r_n}$ is high.

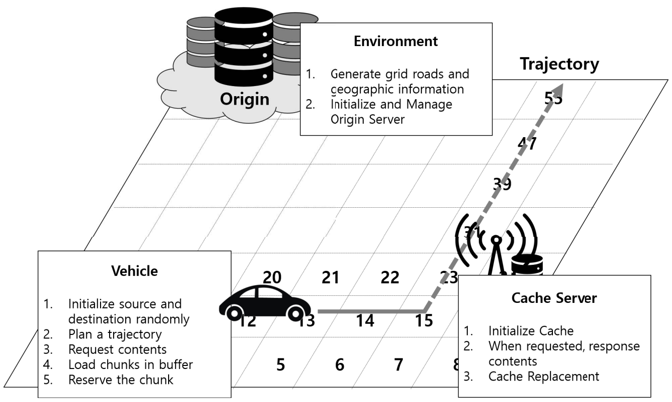


Fig. 10. Overview of grid road edge simulator.

When cache replacement is needed, the cache server retrieves chunk weight values and vectors collected from the vehicles in V2X AS. The cache server compares the values and chooses the chunk that has a high probability to be requested at the cache server. $\vec{ec}$ indicates a position vector between cache server and chunk n. The cache server selects the proper chunk n^* that maximizes the dot product of weight vector and position vector. The optimal chunk can be formulated as follows:

$$n^* = \arg\max_{n} \vec{ec} \cdot (\vec{w_n}) . \tag{5}$$

For an efficient response to a subsequent request, the cache replaces chunks according to the weighted eviction policy described above. Each chunk has the reservation weight. If chunks need to be fetched from the upper layer, it searches through whole chunks and evicts the least weighted chunk from the cache.

IV. Evaluation

In this section, we evaluate the proposed system through extensive simulations and real experiments with autonomous driving functions [35] on the road. The experimental driving platform was equipped with UBLOX 6M GPS and an Edmund camera. The GPS samples geometric information every second. We build a point cloud map using Velodyne VLP-32C.

A. Contents Replacement Strategy

To verify the proposed architecture and algorithm, we model and implement our Manhattan grid simulator. The simulator can generate road grids, vehicles, and a cache server based on input variables. As shown in Figure 10, the simulator consists of three objects: environment, a vehicle, and a cache server. The environment object can generate multiple players such as vehicles and caches and measure vehicular mobility and content delivery. The vehicle generates a path plan randomly according to traffic conditions and communicates with the nearest cache server to obtain geographical content. The cache server transmits the chunks requested when a cache hits; otherwise, it replaces and reorganizes caches. In our proposed method, each vehicle disseminates reservation messages for future chunks and the origin server merges and calculates the weight value and direction of each chunk.

TABLE III
PQI List of NR Sidelink

Resource Type	PQI Value	Packet Delay Budget	Packet Error Rate
GBR	21	20 ms	10^{-4}
	22	50 ms	10^{-2}
	23	100 ms	10^{-4}
Non-GBR	55	10 ms	10^{-4}
	56	20 ms	10^{-1}
	57	25 ms	10^{-1}
	58	100 ms	10^{-2}
	59	500 ms	10^{-1}
Delay Critical GBR	90	10 ms	10^{-4}
	91	3 ms	10^{-5}

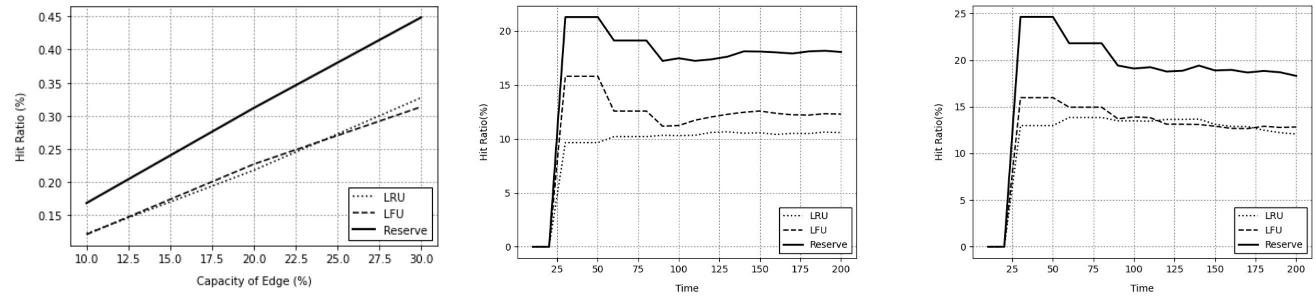
We compared the proposed algorithm to classic cache replacement methods, e.g., LRU and LFU. LRF and LFU decide admission and eviction based on requested time and number. Researchers have tried to apply classical methods to vehicular content-centric networks [55]. First of all, we measured the effect of the edge storing capacity. The cache server without replacement stores chunks based on geographic information, i.e., the nearest chunks from the server, and maintains chunks without any change. Capacity of edge refers to the number of maps stored in each edge among all the maps. If the cache server is assumed to possess 10% of maps, hit ratios of classical methods score 12.21% and 12.08%, as shown in Figure 11(a). The proposed algorithm achieves the 16.83% hit ratio when the cache server possesses 10% of the entire contents.

When the edge server starts to serve, storage is empty. It will be filled with content by the initialization policy. The cache server initiates the contents according to initialization policy such as random and the nearest selection. Geospatial initialization guides the edge server to store the nearest content from the position of the server. Figure 11(b) represents the effect of spatial cache initialization to store the nearest chunks and Figure 11(c) shows the result of random initialization. In the case of the proposed method, random initialization is better than spatial initialization. LRU and LFU also achieved higher hit ratio by random initialization. However, the initialization policy did not have a big effect on improving the hit ratio performance of the proposed method.

The vehicle storage is determined based on a trade-off between energy consumption, weights, and cost. According to Figure 12(a), LRU and LFU are not affected by vehicle buffer size. The greater the vehicle buffer increase, the hit ratio of caching by reservation is measured 25.66% in the case of 10 chunks buffer size.

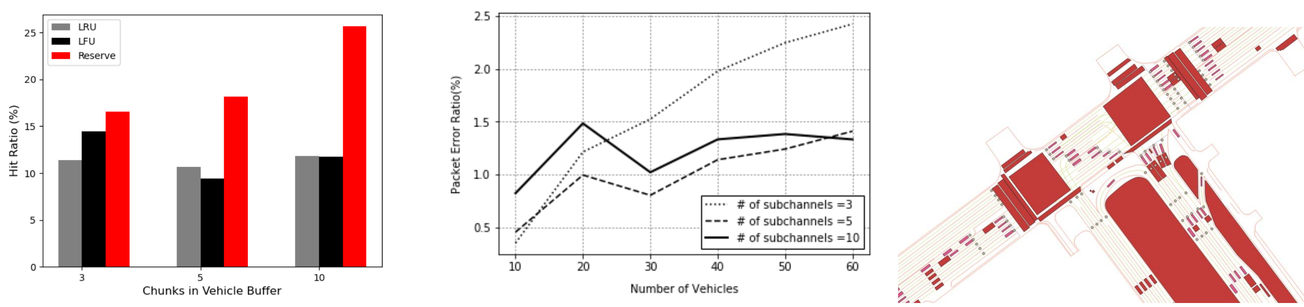
B. V2X Characteristics

The dissemination of V2X sidelink communication has the characteristic that it is unnecessary to resolve the host address and route. Consequently, content can be delivered simultaneously to multiple destinations quickly. However, sidelink channel resources are affected by the number of allocated wireless channels and the vehicle density. According to 3GPP TS 23.287, QoS is required to satisfy the specification listed in Table III.



(a) Cache replacement. (b) Geospatial cache initialization. (c) Random cache initialization.

Fig. 11. Performance of reservation-based caching strategy. To compare the performance of the proposed method with conventional methods, the experiments were conducted by changing the capacity of edge and initialization policy.



(a) (b) (c)

Fig. 12. (a) Hit ratio to size of vehicle buffer. (b) Packet Error Ratio to vehicle popularity by ns-3. (c) HD map of Yeouido (Latitude: 37.5289, Longitude: 126.9169).

TABLE IV
PARAMETER OF NS-3 SIMULATION

parameter	value
Index of MCS	20
size of sub-channel	10 MHz
length of Packets	300 Bytes
UE Tx Power	23 dBm

TABLE V
SPECIFICATION OF EXPERIMENTAL DEVICES

Device	Client	Edge Server	Core Server
Type	Laptop	SBC	Server
Memory	8GB	4GB	256GB

To verify the relationship between PER and Radio environment, we model vehicular communication environments using a network simulator, ns-3 C-V2X [56]. Table IV lists the parameters of simulation. We evaluate the packet error ratio depending on the number of sub-channels and vehicles on the road.

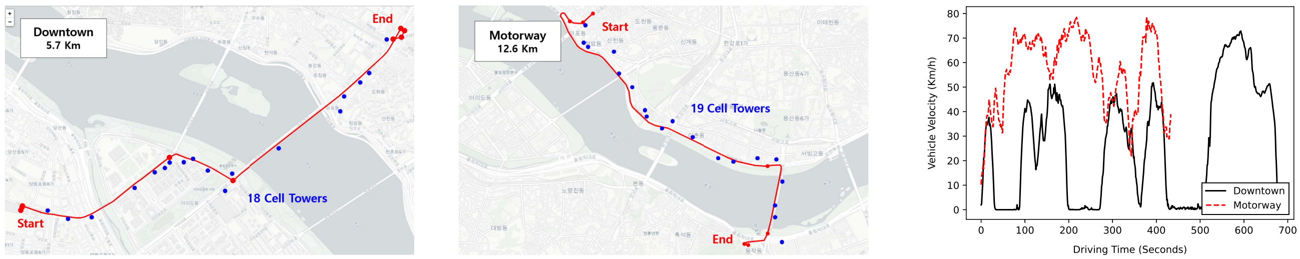
Figure 12(b) shows the results of simulation. The higher the number of vehicles disseminating packets, the greater is the Packet Error Rate increase over requirement of specification. In the case of 3 sub-channels, the PER increases as the number of vehicles increases, which means that 3 sub-channels are not enough resources for communication. Although there are local peaks at 20 vehicles due to stochastic error rate of communication, packet success stays stable when the vehicular network allocates 5 and 10 sub-channels for PC5 interface.

C. Edge Performance in Driving on the Road

To prove the efficiency of the edge network in a real road environment, we implemented vehicular client and HD map servers on the core and edge. The vehicular client estimates vehicular dynamics and records trajectory. Table V lists the specifications of each device. The vehicular client communicates with core server via LTE network and with edge server via a IEEE 802.11a wireless network. Core Server is located over Internet Service Provider and equipped with logical 72 computing processors and an embedded NoSQL Database, MongoDB, which supports geometric queries.

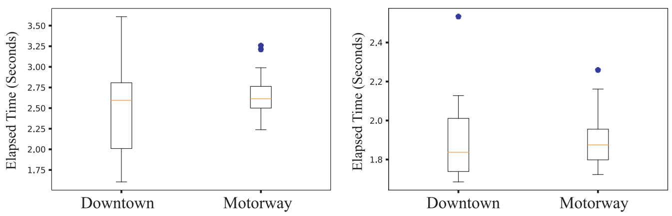
Core Server contains entire HD maps and operates a REST API web server process by Flask, which pushes the chunks of maps to the edge server or vehicular client whenever content is requested. Maps are divided into 2 km × 2 km areas and layered by context including Lane, Link, Nodes, and Surf Signs. The size of each context layer of chunk is approximately 20 MB. Figure 12(c) shows the example of the requested HD map [57].

The experiment is performed in two varied scenarios, which are at a downtown and a motorway for the purpose of comparison with different road conditions. As shown in Figure 13(a), the downtown scenario runs through Yeouido business district and Han River and encounters 18 LTE cell towers, with the total distance being 5.7 km. As shown in Figure 13(b), the motorway scenario runs through Gangbyeonbuk-ro motorway along the northern Han River side. The vehicle encounters 19 LTE cell towers. The total distance is 12.6 km. The Vehicle client equipped with UBLOX 6M GPS sensor samples geometric information every second. The client measures positions and velocities at each waypoint. In the downtown scenario,



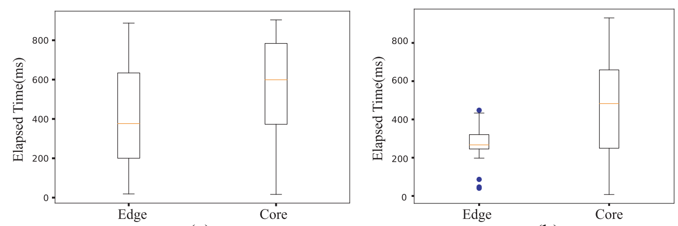
(a) Downtown Trajectory (b) Motorway Trajectory (c) Velocities

Fig. 13. Two trajectories of driving experiments, where red lines indicate the path of the vehicle and blue dots represent locations of cell towers.



(a) (b)

Fig. 14. A blue point represents an outlier in the box plot. (a) Elapsed time of core server. (b) Elapsed time of edge server.



(a) (b)

Fig. 15. A blue point represents an outlier in the box plot. (a) Elapsed time of edge and core server for point cloud. (b) Elapsed time of edge and core server for image.

each cell tower serves the vehicle for approximately 35 seconds. In the motorway scenario, it takes 22 seconds, which shows that the handover occurs more frequently in the high velocity environment.

Figure 13(c) represents the amount of change in vehicle movement during a driving scenario. In the downtown scenario, the vehicle tends to stop and go alternately, but keeps moving over 40 km h^{-1} velocity in the motorway.

Vehicle clients are connected to Core and Edge HD Map server and request map content every 10 seconds to measure the performance of content delivery.

$$T_{Elapsed} = T_{Request} + T_{Process} + T_{Response}, \tag{6}$$

where the elapsed time to query REST API server consists of request delivery time $T_{Request}$, content processing time on server $T_{Process}$, and response delivery time $T_{Response}$ [58].

When the server receives an HTTP request message, it parses a message and searches requested records in Mongo Database system. The processing time depends on computing resources of the device. The core server with 72 computing processors takes 740 ms, whereas the edge server with 4 computing processors takes 1500 ms to query the database.

As shown in Figure 14(a), elapsed time to query to core network server through internet network was measured to be a median of 2.58 s in the downtown scenario and 2.66 s in the motorway scenario. The downtown scenario showed higher variance of time than the motorway scenario. It can be assumed that various variables in the downtown, such as massive pedestrians and other vehicles, cause an instability of network performance.

As shown in Figure 14(b), the round-trip time to the edge server is 1.9 s in the downtown and 1.89 s in the motorway, when there is no significant difference between the two scenarios. Storing content on the edge can significantly shorten the time to request and receive content, while guaranteeing the stable network quality even in variable environments.

D. Edge Performance on 3D Point Clouds Caching for Localization for Autonomous Driving

Vehicle localization by 3D point clouds acquired by LiDAR sensors are widely used in autonomous driving [23], [59]. However, they require a larger storage capacity than other content, such as semantic maps and 2D images. To meet the real-time constraint, a vehicle should load point cloud maps on its trajectory. However, it is difficult to load new content immediately when the trajectory changes unexpectedly.

A point cloud map is usually generated by registering consecutive scan data from LiDAR. We built the point cloud map with Velodyne VLP-32C and split it into several map chunks. We assume that a vehicle receives map chunks from the edge server and executes the localization task through them. Specifically, a unit chunk contains points over a 100 m × 100 m area and are resolved by 10cm × 10cm. The size of the chunk is 40MB. The edge server contains chunks and responds to the requests of vehicles. Vehicles compare the current local scene from LiDAR to map chunks and estimate the precise position of the vehicle.

As with Section IV-C, the experiment is performed on the urban road with an average speed of approximately 60 km h^{-1}. The vehicle requests content from the point cloud to the core and edge server, respectively. Each server delivers content through TCP bytes stream. The vehicle client measures the elapsed time through the network and delivers them to the localization module.

Figure 15(a) shows that the median elapsed times of the edge and core server are 376 ms and 599 ms, respectively. The localization process returns the result approximately within 100 ms. The delivery through the edge server is 25.7% faster

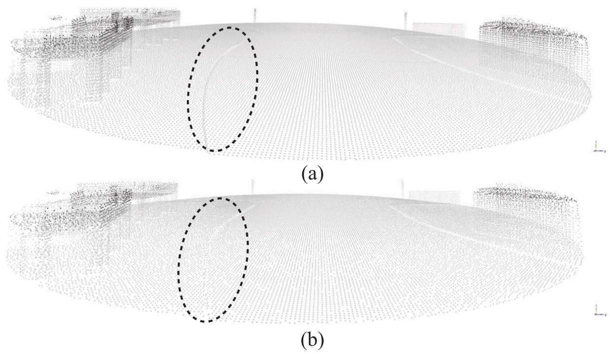


Fig. 16. (a) A point cloud map chunk through edge server. (b) A point cloud map chunk through core server. Dotted ellipsoids refer to the road boundary area such as curbs and sidewalks.

than through the core server. Therefore, fast delivery through the edge server can generate dense point cloud map chunks and help to estimate the precise position. In general, geometric features such as an edge and a corner point are useful features for vehicle localization. More geometric features can be extracted as the density of point clouds increases. Hence, edge information such as road boundaries can be easily extracted from the dense point cloud map chunk obtained through the edge server as shown in Figure 16(a). In contrast, it is hard to extract edge information from the sparse point cloud map chunk obtained through the core server because road boundaries are smoothed as shown in Figure 16(b). As described above, each chunk contains information of 100 m, where it takes 6 s to consume a chunk if a vehicle drives at 60 km h^{-1}. This experiment shows that our proposal supports the HD maps and localization requirements for autonomous driving.

E. Edge Performance on Images Caching for Detection for Autonomous Driving

We also evaluate the proposed method with image data that are often shared over V2I or V2V [3] for recognition tasks. We obtain image data using our platform [35]. The size of each image is approximately 0.5MB and the spatial size is 1920×1200 pixels. We measure the elapsed time from the test vehicle to the core and edge server, respectively over the same trajectory in Section IV-D. The number of the requests to the core and edge server are 278 and 314, respectively. The median elapsed times of the core and edge server are 482 ms and 266 ms, respectively as shown in Figure 15(b), which means that our method can send the image data more effectively than through the core server. Although some elapsed times are above the maximum in the box plot, the outliers can be easily detected by the thresholding process and the multi-modal sensors installed on the platform prevent serious accidents by backing up this situation. Additionally, the standard deviations of the elapsed time for the core and edge server are 237.44 and 64.78, respectively. This indicates that the delivery through the cache server shows stable performance. It is imperative to achieve low-standard deviation of the elapsed time in autonomous driving systems because the unpredictable elapsed time can cause fatal accidents.

V. Conclusion

As autonomous vehicle technology becomes a reality, further evolution of vehicle communication is required to satisfy the requirement of reliability and performance. Compared to conventional communication methods, vehicle communication has different characteristics, which are based on mobility and geospatial features. HD map is the representative example of vehicular content. For HD map delivery of autonomous vehicles, we researched vehicular communications and new emerging communication trends, such as 5G new radio and Content-Centric Network (CCN).

In this paper, we proposed an architecture and a cache replacement algorithm for V2X mobile edge. NR V2X supports sidelink and uplink communication, where the vehicle chooses the appropriate method based on environmental conditions.

We analyzed the newly released NR V2X specification and defined the role and procedure of V2X entities. Unlike conventional caching algorithms, consumers generate a reservation message for hit cache in the future. As the V2X application server orchestrates the reservation information, the edge cache server can pull appropriate candidate chunks with high possibility to hit cache. Edge storage can reduce the time to deliver content and load on the core. In two driving scenarios, content delivery through the edge server guarantees a reliable quality of service.

The proposed method improves the hit ratio performance more than other classic caching algorithms, where 16.33% of requests hit the adjacent cache server in the condition of 20 chunks stored in the cache. The larger the size of cache storage and vehicle buffer increase, the higher the improvement in performance, where the content delivery time can be reduced. We tested the architecture and method in autonomous driving scenarios using real data and experiments and demonstrated that it can contribute to the efficiency of vehicular content delivery via C-V2X.

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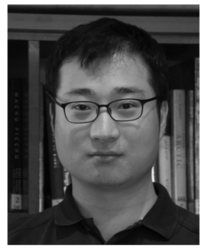

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