Trustworthy Foundation for CAVs in an Uncertain World: From Wireless Networking, Sensing, and Control to Software-Defined Infrastructure

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Abstract:

Three basic enablers for connected and automated vehicles (CAVs) are wireless networking, sensing, and control. Tightly coupled with the physical process of wireless signal propagation, vehicle movement, and environment, however, CAV wireless networking, sensing, and control are subject to complex cyber-physical uncertainties. To address the challenges, we propose an integrated, cross-layer framework for taming cyber-physical uncertainties, within which we develop novel algorithms and methodologies for addressing the interdependencies between networking, sensing, control, and physical processes. To enable high-fidelity evaluation and thus the deployment and adoption of new CAV technologies, we develop a software-defined CAV infrastructure for conducting CAV experiments using vehicles in real-world traffic so that properties of V2X communication, vehicles, traffic, road, and environment are captured at high-fidelity.

1 Introduction

Transforming the traditional, single-vehicle-based safety and efficiency control, next-generation vehicles will cooperate with one another and with transportation infrastructures to ensure safety, maximize fuel economy, and minimize emission as well as congestion. Three basic enablers for this vision of connected and automated vehicles (CAVs) are wireless networking, sensing, and control: wireless networking enables real-time sensing and control within the ecosystem of vehicles, infrastructures, and environment; networked sensing enables comprehensive, beyond-line-of-sight sensing for optimal CAV control; networked control enables intelligent action upon the real-time information across the ecosystem of infrastructures and vehicles [1].

Tightly coupled with the physical process of wireless signal propagation, vehicle movement, and environment, however, CAV wireless networking, sensing, and control are subject to complex dynamics and uncertainties in both the physical domain and the cyber domain. In the *physical* domain, multipath signal propagation and power attenuation introduce anisotropy, asymmetry, and complex spatiotemporal dynamics in wireless communication; together with wireless interference, they introduce uncertainties in the reliability, timeliness, and throughput of wireless communication. Vehicle mobility introduces dynamics in vehicle spatial distribution, thus further increasing the uncertainty in wireless channel properties. Additionally, CAV sensing and control are subject to uncertainties in the physical environment such as bad weather, sharp turns, and location-specific vehicle traffic pattern. In the *cyber* domain, dynamics in wireless networking, sensing, and control interact with one another during their adaptation to physical dynamics. For instance, the real-time capacity (i.e., amount of data deliverable within a certain time duration) of wireless networking changes during its adaptation to physical-domain dynamics; accordingly, CAV sensing and control adapt their optimal strategies to the in-situ network real-time capacity. Dynamic sensing and control strategies in turn generate dynamic network traffic pattern (e.g., load) and pose dynamic requirements on data delivery reliability, timeliness, and throughput. These complex dynamics and uncertainties, together with the real-time, safety-critical nature of CAV sensing and control, require us to rethink the theory and practice of wireless networking as well as vehicle sensing and control.

To address the challenge, we propose an integrated, cross-layer framework for taming cyber-physical uncertainties in CAV wireless networking, sensing, and control as shown Figure 1. In this framework, wireless networking, sensing, and control interact with one other to address cyber-physical uncertainties. Based on the real-time capacity region of wireless networking and the physical process of vehicle movement, traffic, and environment, CAV sensing and control select their

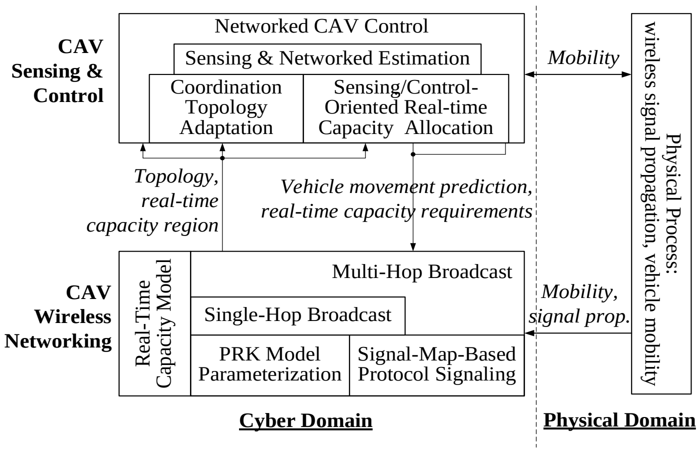

Figure 1: Integrated, cross-layer framework for CAV wireless networking, sensing, and control

optimal strategies and the corresponding requirements on the timeliness and throughput of wireless data delivery (e.g., for maximizing sensing accuracy and roadway utilization while ensuring safety). Based on the requirements from CAV sensing and control, wireless networking adapts to cyber-physical uncertainties to ensure the timeliness and throughput of V2X communication; for addressing the impact of vehicle mobility on wireless communication, wireless networking also leverages input from vehicle control on vehicle movement prediction.

As new CAV technologies are developed, they need to be evaluated before their real-world deployment and adoption. The impact of vehicle traffic, road, and environmental conditions (e.g., buildings) on CAV wireless communication and the safety-critical nature of vehicle operation require evaluating CAV technologies and applications in real-world settings. Thus it is desirable to conduct CAV experiments using vehicles in real-world traffic so that properties of V2X communication, vehicles, traffic, road, and environment are captured at high-fidelity. To realize this paradigm of symbiotic CAV experiments in real-world traffic, we develop a software-defined CAV infrastructure through software-defined virtualization (SDV) and multi-domain emulation (MDE) of CAVs.

The rest of this chapter is organized as follows. In Sections 2, 3, and 4, we elaborate on our recent progress in CAV wireless networking, control, and software-defined infrastructure, and we make concluding remarks in Section 5.

2 Predictable CAV wireless control networking

In CAV wireless networking, the cyber-physical uncertainties challenge the models and protocols for scheduling concurrent transmissions to control co-channel interference, which is a basic issue in wireless networking and affects the predictability in data delivery reliability, timeliness, and throughput [2, 3]. For agile adaptation to dynamics and uncertainties, distributed scheduling is desirable in vehicular wireless networking. Nonetheless, most existing literature are either based on the protocol interference model or the physical interference model, neither of which is a good foundation for distributed interference control in the presence of dynamics and uncertainties [2, 3]. To address this issue, we have proposed the *physical-ratio-K (PRK)* interference model that integrates the protocol model's locality with the physical model's high-fidelity [2]. In the PRK model, a node $C^{'}$ is regarded as not interfering and thus can transmit concurrently with the transmission from another node S to its receiver R if and only if

$$P(C^{'},R) < \frac{P(S,R)}{K_{S,R,T_{S,R}}}$$

where $P(C^{'},R)$ and $P(S,R)$ is the average strength of signals reaching R from $C^{'}$ and S respectively, $K_{S,R,T_{S,R}}$ is the minimum real number (i.e., can be non-integer) chosen such that, in the presence of interference from all concurrent transmitters, the probability for R to successfully receive packets from S is no less than the minimum link reliability $T_{S,R}$ required by applications (e.g., CAV control). As shown in Figure 2, the PRK model defines, for each link (S,R), an exclusion region $\Lambda_{S,R,T_{S,R}}$ around the receiver R such that a node $C \in \Lambda_{S,R,T_{S,R}}$ if and only if $P(C',R) \geq \frac{P(S,R)}{K_{S,R,T_{S,R}}}$. Accordingly, every node $C \in \Lambda_{S,R,T_{S,R}}$ is regarded as interfering with and thus shall not transmit concurrently with the transmission from S to R.

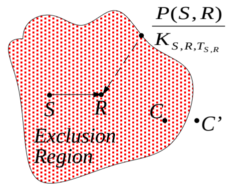

Figure 2: Physical-ratio-K (PRK) interference model

For enabling predictable interference control in the presence of network and environmental uncertainties, the parameter $K_{S,R,T_{S,R}}$ of the PRK model adapts to the specific network and environmental conditions to ensure the application-specific link reliability requirements. By ensuring the required link reliability and by using signal strength instead of geographic distance in model formulation, the PRK model captures the properties of wireless communication (e.g., cumulative interference and anisotropic signal propagation) and thus is of high-fidelity. For enabling distributed protocol design and implementation, the PRK model is also local [2, 3]: 1) The parameters of the PRK model are either locally measurable (i.e., for the signal strength and link reliability between close-by nodes) or locally controllable (i.e., for $K_{S,R,T_{S,R}}$ of each link (S,R)), thus PRK-based scheduling does not need to rely on parameters such as nodes' locations or channel path loss between far-away nodes which are often used in physical-model-based scheduling but are difficult to obtain precisely, especially in a distributed manner; 2) Only pairwise interference relations between close-by nodes need to be defined in the PRK model, thus PRK-based scheduling does not require explicit global coordination which is often used in physical-model-based scheduling. Through comprehensive analysis, simulation, and measurement, we have observed that, by ensuring the required link reliability, PRK-based scheduling also helps reduce data delivery delay by minimizing the need for packet retransmissions; we have also found that PRK-based scheduling can enable a channel spatial reuse very close to (e.g., >95%) what is feasible in physical-model-based scheduling while ensuring application-required reliability [2]. Therefore, the PRK model serves as a good foundation for predictable interference control.

A basic task in PRK-based scheduling is to instantiate the PRK model, i.e., identifying the parameter $K_{S,R,T_{S,R}}$ for every link (S,R), according to in-situ, potentially unpredictable network and environmental conditions. It is, however, difficult to characterize the relation between $K_{S,R,T_{S,R}}$ and the packet delivery reliability along (S,R) in closed-form, and the relation is complex and dependent on network and environmental conditions which may well be unpredictable at design time [2]. To address the challenge, we observe that the PRK model instantiation problem can be formulated as an online *regulation control* problem [4], where the ``plant" is the link $(S,R)$, the ``reference input" is the required link reliability $T_{S,R}$, the ``output" is the actual link reliability $Y_{S,R}$ from $S$ to $R$, and the ``control input" is the PRK model parameter $K_{S,R,T_{S,R}}$. Then we can leverage minimum-variance regulation control theory [4] to derive the controller for instantiating the PRK model parameter [3].

Given the instantiated PRK model parameter $K_{S,R,T_{S,R}}$ and using the *local signal map* that contains the average signal power attenuation between R and every node C close-by, R can identify the set of nodes whose transmissions can interfere with and thus cannot be concurrent with the transmission along link (S,R) [3]. With precise awareness of mutual interference relations with close-by nodes/links, nodes schedule data transmissions in a TDMA fashion using our distributed Optimal-Node-Activation-Multiple-Access (ONAMA) algorithm [5] to avoid concurrent transmissions along interfering links [3]; for convenience, we denote the resulting PRK-based scheduling protocol as PRKS [3].

Through extensive measurement study in the high-fidelity Indriya and NetEye wireless network testbeds, we observe the following [3]: 1) The distributed controllers for PRK model instantiation enable network-wide convergence to a state where the desired link reliabilities are ensured; 2) With local, distributed coordination alone, PRKS achieves a channel spatial reuse very close to what is enabled by the state-of-the-art centralized physical-model-based scheduler iOrder [6] while ensuring the required link reliability; 3) Unlike existing scheduling protocols where link reliability is unpredictable and the ratio of links whose reliability meets application requirements can be as low as 0%, PRKS enables predictably high link reliability (e.g., 95%) for all the links in different network and environmental conditions without a priori knowledge of these conditions; 4) By ensuring the required link reliability in scheduling, PRKS also enables a lower communication delay and a higher network throughput than existing scheduling protocols. Therefore, PRKS serves as an effective, field-deployable solution to predictable interference control, which has been an open problem for over 40 years [7], and PRKS enables predictable communication reliability which is a foundation for predictable CAV wireless networking and control in general.

3 CAV control

We employ platoon control to discuss CAV control issues. The early studies of platoons, such as the PATH program in California in 1980s, targeted many fundamental topics, including goals, task division, control architectures, sensing and actuation, and control laws for headway control, *etc.* [8]. Since then, broader issues have been pursued, such as spacing policies, powertrain dynamics, and the impact of homogeneity and heterogeneity; with real world demonstrations, exemplified by GCDC in Netherlands, SARTRE in Europe, and Energy-ITS in Japan.

The earlier platoons employed radar-based sensing systems with highly limited information exchange topologies. The rapid deployment of V2X communications can accommodate various types of information topologies, e.g., two-predecessor following type and multiple-predecessor following type. New challenges naturally arise due to topology varieties, communication time-delay, packet loss, and quantization error. From a cyber system viewpoint, a vehicular platoon is a networked dynamical system with distributed controllers. Within this framework, vehicles in a platoon use their neighborhood information for controller design but must coordinate to achieve a global goal. As proposed by Li *et al.* [9, 10], such a perspective naturally decomposes a platoon system into four interrelated components as shown in Figure 3: 1) Node dynamics (ND), which describes the behavior of each vehicle. The vehicle longitudinal dynamics are represented by nonlinear models of engine, drive line, brake system, aerodynamics drag, tire friction, rolling resistance, gravitational force, *et*c. They are often simplified to linear models in practice, e.g., single integrator model, second-order model (including double-integrator model), third-order model, and single-input-single-out model; 2) Information flow topology (IFT), which defines how the nodes exchange information with each other. The IFT is usually represented and studied by using algebraic graph theory; 3) Formation geometry (FG), which dictates the desired inter-vehicle distances. There exist three major policies of FG: constant distance policy, constant time headway policy, and nonlinear distance policy. The objective of platoon control is to track the speed of the leading vehicle while maintaining a formation governed by the desired spacing policy between consecutive vehicles; 4) Distributed controller (DC), which implements the feedback control using only neighboring information; At present, most DCs are linear for rigorous performance analysis and hardware implementation. Since internal stability of the closed-loop system depends critically on IFTs, linear DC design is often case-

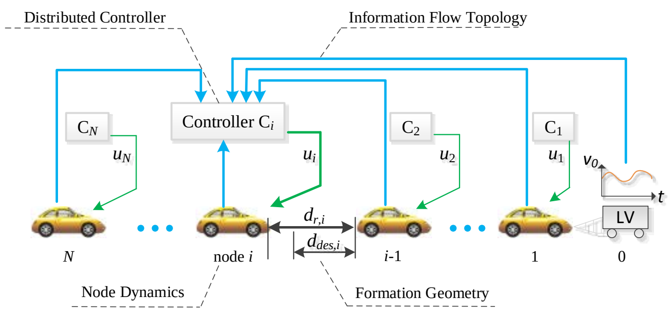

Figure 3: Four major components of a platoon system: node dynamics, information flow topology, formation geometry, and distributed controller. $d_{r,i}$ is the actual relative distance, $d_{des,i}$ is the desired distance, u_i is the control signal for the *i*-th vehicle, and C_i denotes the controller in the *i*-th vehicle.

specific. Linear DCs suffer from difficulties in explicitly ensuring string stability or accommodating state or control constraints. Recently, $\mathcal{H}_\infty$ controller synthesis has been proposed to include the string stability requirement as a priori design specification. In addition, model predictive control (MPC) has been introduced to forecast system dynamics, explicitly handling actuator/state constraints by optimizing given objectives.

Within this four-component platoon cyber-physical system, platoon control aims to maximize highway utility while ensuring zero accident. To increase highway utility, it is desirable to reduce inter-vehicle distances and to accelerate fast towards a new formation after disturbances. These, however, will increase the risk of collision in the presence of vehicle traffic uncertainties. This tradeoff prompts a systematic design to *maximize benefits at a tolerable risk*. Interestingly, this platoon performance problem bears striking similarity to financial portfolio management problems aiming to maximize profit returns with controlled risk, which have been rigorously studied in the mean-variance (MV) framework. Recently, we have applied the MV method to study platoon control [11]. The MV method offers distinct advantages: 1) unlike heuristic methods such as neural networks and genetic algorithms, the MV method is simple but rigorous; 2) the MV method is computationally efficient; 3) the form of the solution (i.e., efficient frontier) is readily applicable to assessing risks in platoon formation, hence is practically appealing.

The MV framework originated from the Nobel-price-winning work of Markowitz [12]. In finance, it enables an investor to seek highest return (mean) under a pre-specified risk level (variance of the return). It has developed into a foundation of modern finance theory and been applied to other fields. Using the stochastic linear-quadratic (LQ) control framework, Zhou and Li [13] studied the MV in continuous-time systems, in which the control weighting matrix is no longer positive definite, departing fundamentally from the traditional LQ problem. By introducing a backward-stochastic-differential-equation (BSDE) in such MV frameworks, one can accommodate indefinite and even negative definite control weights under certain conditions. Optimality of the BSDE design was established by embedding the original problem into a tractable auxiliary problem.

To take into consideration random environments not representable via the usual stochastic differential equation setup, we developed more precise models with possible random switching in regimes [14]; based on these results, we have studied the following models for platoon control.

Switching Diffusion Model: At the cyber level, each vehicle is a node in the network of n_0 vehicles. The node state $x_i(t)$ consists of the vehicle's position, speed, direction, etc. The *i*th vehicle's dynamics can be described by

$$dx_i(t) = f_i(x_i(t),\ u_i(t),\alpha(t))\ dt\ +\ \sigma_i(x_i(t),\ u_i(t),\alpha(t))\ \ dw_i, \qquad i = 1,\dots,n_0$$

$\alpha(t) \in M$, where the first and second terms represent vehicle dynamics and noise effects, respectively; $w_i(\cdot)$ is a standard Brownian motion; u_i is the control for the *i*th vehicle. The switching network topology *G* is a Markov chain $\alpha(\cdot)$, taking values in $M = \{1,\dots,m_0\}$ with generator *Q* which is independent of the Brownian motion $w(\cdot) = \left(w_1(\cdot),\ldots, w_{n_0}(\cdot)\right)^T$. At time *t*, a vehicle uses the available neighborhood information from the graph $G(\alpha(t))$ to adjust its control $u_i(t)$. For each $\alpha(t) \in M$, the drift $f_i(x_i(t), u_i(t),\alpha(t)) : R \times R \mapsto R$ delineates the "average behavior" of the dynamics, and $\sigma_i(x_i(t), u_i(t),\alpha(t)) : R \times R \mapsto R$ tells us the ``standard deviation" of the dynamics about its mean. Acting as the intensity of the noise, σ_i is referred to as *diffusion coefficient* in probability.

If σ_i is large, the system displays a wide range of fluctuations. If the noise is sufficiently small, the system is represented by a dynamic system with only the drift term. When the random disturbances disappear completely, the system reduces to a deterministic system that does not include the Brownian motion part. Then, the interconnected systems can be represented by a hybrid stochastic system

(1) $dx(t) = f(x(t), u(t),\alpha(t))\, dt + \sigma(x(t), u(t),\alpha(t))\, dw,$

where $x(t) = (x_1(t),\ldots, x_{n_0}(t))^T \in R^{n_0}$, $u(t) = (u_1(t),\ldots,u_{n_0}(t))^T \in R^{n_0}$, w is a n_0-dimensional standard Brownian motion, $f(x, u,\alpha) = (f(x_i, u_i,\alpha)) \in R^{n_0}$, $\sigma(x, u,\alpha) = \mathrm{diag}(\sigma_i(x_i, u_i,\alpha)) \in R^{n_0 \times n_0}$. Since the Markov chain $\alpha(\cdot)$ takes values in a set of isolated points, it is a discrete event process. Thus the system framework is a hybrid switching diffusion, in which continuous vehicle dynamics and discrete topology switching events coexist. To date, such switching models has only been used to treat networked platoon control in our work [11], especially when delays are involved. In addition, we can also study a switching jump diffusion model as proposed in our recent work. The switching jump diffusion model is similar to (1) but with an additional Poisson jump term $k(\cdot)$, which is used to model short noise and sudden burst of noise not representable by the usual Brownian motions.

MDP Formulation: At a given instant *t*, if $\alpha(t) = i$, then $G(\alpha(t)) = G(i)$, namely the topology switches according to the values of $\alpha(t)$. Given $\alpha(t) = i$, the dynamics of the platoon are given by a controlled Markov chain *x(t)* instead of a differential equation. *x(t)* takes values in R^{n_0}, which is another continuous-time Markov chain with general state space $M_1 \subset R^{n_0}$ and generator *Q(u,i)* that is control dependent. This controlled Markov chain is a Markov decision process. Once the state *i* is fixed, its dynamics are completely determined by the generator. This formulation differs from the standard setup of MDPs in that the generator *Q* is not only *u*-dependent, but also α-dependent (i.e., $Q = Q(u,\alpha)$). Thus, we write it as

(2) $x \sim Q(u,\alpha), \alpha \in M, M_1 \subset R^{n_0}$

Here, the state space may be uncountable or a subset of R^{n_0}, which is more general than the MDP formulations with either a finite or countable state space.

These two formulations have their own pros and cons. The switching diffusion model contains detailed descriptions of the system dynamics and its solution is associated to certain differential equations. The Markov decision process uses distributed information in which the controlled Markov chain has control-dependent generators, leading to a simplified model structure.

Mean-variance control for utility-safety management: With dynamics described by either the switching diffusion (1) or by the Markov decision process (2), we can define the mean-variance platoon distribution control problem. Motivated by our recent work, our main objective is to achieve platoon formation in a short horizon, in which the associated dynamic programming equation is time dependent. Let $U(\cdot): R^{n_0} \mapsto R$ be a sufficiently smooth and concave utility function based on factors such as inter-vehicle distances. Our objective is to find an admissible strategy $u(\cdot)$ among all the admissible actions whose expected terminal value is $E\ U(x(T)) = U(z)$ for some given $z \in R^{n_0}$, and the risk as measured by the variance of the terminal wealth (i.e., $\mathrm{Var}U(x(T)) \equiv E[U(x(T)) - EU(x(T))]^2 = E[U(x(T)) - U(z)]^2$) is minimized.

Then the mean-variance problem is a constrained stochastic optimization problem, parameterized by $z \in R$:

$$
(3) \qquad \begin{cases} J\left(x_0, i_0, u(\cdot), \lambda\right) = E\left|U(x(T)) - U(z)\right|^2, \\ \text{subject to } EU\ \left(x(T)\right)\ =\ U\left(z\right),\ (x(\cdot), u(\cdot)) \text{ admissible} \end{cases}
$$

The problem is called feasible if there is at least one strategy satisfying the constraint. It is said to be finite if it is feasible and the infimum of $J\left(x_0, i_0, u(\cdot)\right)$ is finite. An optimal strategy to the above problem, if it exists, is said to be an efficient strategy corresponding to $U(z)$, and the corresponding $Var(U(x(T)), U(z))$ and $(\sigma_{U(x(T))}, U(z))$ are interchangeably called an efficient point, where $\sigma_{U(x(T))}$ denotes the standard deviation of $U(x(T))$. The set of all the efficient points is called the efficient frontier.

4 Software-defined CAV infrastructure

As new CAV technologies (e.g., CAV communication with predictable reliability [2, 3]) are developed, we need to evaluate these technologies in real-world settings before the enabled new CAV applications can be deployed for real-world use, thus requiring a methodology for enabling the spiral innovation process of research, development, pilot deployment, and adoption. CAV is inherently an interdisciplinary field involving multiple disciplines such as transportation, communication, and control, it is thus important for different disciplines to collaborate in the innovation process for the concerted progress in all dimensions of CAV technologies [15].

As shown in Figure 4(a), vehicle technologies have traditionally been researched, developed, and evaluated using a few test vehicles, and then the technologies can be deployed in real-world settings at scale since the individual vehicles are controlled separately without communicating with one another. With CAVs, however, this innovation paradigm has inherent drawbacks since the testing with a few vehicles in selected test settings does not capture CAV communication behavior and its impact on CAV safety, efficiency, and comfort in real-world deployment of a large number of vehicles in potentially unpredictable traffic, road, and environmental conditions. To address this issue, the USDOT Safety Pilot Model Deployment of connected vehicles (CVs) and the planned large scale CV pilot deployments employ thousands of test vehicles in real-world settings. While these deployments enable transportation research such as understanding the benefits of CVs for the safety and efficiency of road transportation, these deployments do not enable the testing of technologies in other important dimensions of CAVs, for instance, the testing of new CAV networking and control technologies. Accordingly, these deployments cannot serve as experimental infrastructures for the research communities of different CAV disciplines to collaborate with one another. For continuous, cross-disciplinary innovation and evolution of CAV technologies, there still lacks methodologies that enable a symbiotic innovation paradigm where, as shown in Figure 3(b), research experiments from multiple CAV disciplines may co-exist with one another and with existing CAV technologies and applications in real-world traffic [15].

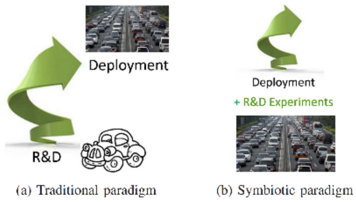

Figure 4: Vehicle innovation paradigms

Towards enabling the symbiotic innovation paradigm for continuous, cross-disciplinary CAV evolution, we develop a software-defined CAV infrastructure through software-defined virtualization (SDV) and multi-domain emulation (MDE) of CAVs. SDV partitions each CAV sensing, computing, and networking equipment into multiple ``slices" such that the sensing, computing, and networking tasks of a CAV experiment and those of the existing CAV applications can execute in different slices without interfering with one another, thus enabling the use of vehicles in real-world traffic to support CAV experiments. SDV dynamically allocates sensing, computing, and networking resources among CAV experiments and existing applications according to the requirements of CAV experiments and applications, and, by allowing the research communities of different CAV disciplines to share a same experimental infrastructure, SDV enables cross-discipline collaboration and coordination in the spiral CAV innovation process. By deploying and executing the ``field" components of CAV emulation as CAV experiments in vehicles, SDV also enables integrating vehicles in real-world traffic with multi-domain simulation of V2X communication, vehicle dynamics, and traffic flow in high-performance cloud computing infrastructures, thus integrating the high-fidelity of real-world vehicle traffic with the flexibility and scalability of in-cloud simulation. To leverage existing accomplishments from different CAV communities and to facilitate cross-discipline collaboration, our multi-domain emulation (MDE) system develops mechanisms for integrating the state-of-the-art network simulator ns-3 and vehicle as well as traffic dynamics simulator SUMO into a holistic CAV emulation system where different CAV communities can contribute to different parts of the emulation system and leverage capabilities developed by other communities [15].

To demonstrate our software-defined CAV infrastructure and to evaluate its effectiveness, we study CAV technologies and applications in public safety which has not been well explored as an application domain of CAVs. In particular, we deploy our SDV-based CAV platforms in the police patrol vehicles of Wayne State University. Together with GENI networking and cloud computing infrastructures, these police patrol vehicles effectively support the real-world application of 3D-vision-based public safety surveillance and MDE-based CAV experiments at the same time, thus enabling symbiotic experiments of emerging CAV technologies and applications in real-world vehicle traffic of existing CAV technologies and applications for public safety, which we expect to speed up the evolution and adoption of CAV technologies and applications [16].

5 Concluding remarks

In this chapter, we have reviewed the challenges that cyber-physical dynamics and uncertainties pose to CAV wireless networking, sensing, and control, and we have proposed an integrated, cross-layer framework for establishing a trustworthy foundation for CAVs. To realize the integrated framework, we have made initial progress towards an algorithmic and methodological foundation for CAV wireless networking and control. For enabling continuous CAV evolution, we have also developed a software-defined CAV infrastructure for symbiotic CAV experiments and real-world deployments as well as for cross-discipline collaboration in CAV innovation. These algorithms, methodologies, and software-defined infrastructures enable the development and deployment of CAV solutions. Interesting future work include, but are not limited to, extending the PRKS wireless transmission scheduling algorithm to address vehicle mobility in CAV networks, joint optimization of CAV networking, sensing, and control, and integrating the open-source driving simulator OpenDS into our software-defined CAV infrastructure.

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