Critical Roles of Control Engineering in the Development of Intelligent and Connected Vehicles

Journal of Intelligent and Connected Vehicles
2024, **7**(2): 79–85
https://doi.org/10.26599/JICV.2023.9210040

Editorial

Critical roles of control engineering in the development of intelligent and connected vehicles

Yang Fei[1], Peng Shi[2,3], Yang Liu[4], Liang Wang[1,✉]

[1]*School of Vehicle and Mobility, Tsinghua University, Beijing 100084, China*
[2]*School of Electrical and Mechanical Engineering, The University of Adelaide, Adelaide SA 5005, Australia*
[3]*Research and Innovation Centre, Obuda University, Budapest 1034, Hungary*
[4]*Department of Architecture and Civil Engineering, Chalmers University of Technology, Gothenburg SE-41296, Sweden*

Received: January 19, 2024; Revised: March 4, 2024; Accepted: March 6, 2024

1 Introduction

In recent years, advancements in onboard computing hardware and wireless communication technology have remarkably stimulated the development of intelligent and connected vehicles (ICVs). Specifically, some researchers have investigated the issue of employing various advanced control techniques to optimize the performance of autonomous vehicles in practice (Sun et al., 2023; Zhang et al., 2023a, 2023b). Therefore, this article aims to discuss why and how control engineering plays an essential role in the development of ICVs.

To live up to intelligent and connected characteristics, a vehicle should possess four abilities (Fig. 1): the ability to sense, communicate, make decisions and actuate. The ability to sense enables machines to abstract knowledge from their surroundings. Intersystem communication weaves networks that integrate fragmented information collected by individual vehicles. Decision-making modules are responsible for finding the current optimal choice, while actuating modules interpret decisions into signals that actuators can understand to manipulate system states accordingly. Apart from decision making, all other aspects are closely correlated with control theories and their applications.

There are currently two main problems for sensing: (1) obtaining more accurate results based on data collected from multiple sources and (2) estimating states that are not measured or measurable. The key to the first issue is to find the optimal weighting strategy among the many sources we have, and the problem is classified as a state filtering problem. The second question is relatively difficult because we can only use the correlation among known states and unknown states to “guess” the unknown factors.

Wireless communication is essential for constructing networked autonomous vehicles. Although 4G techniques can guarantee a data transmission speed of 100 MB per second in theory, we still cannot model networked vehicles as nodes with unlimited bandwidth due to the various types of data (videos, point cloud data, etc.) and the potentially high number of vehicles within a specific neighborhood.

Robust motion control methods are the foundation of multi-vehicle cooperation such as platooning, formation control, drone-based parcel delivering, and dynamical inter-vehicle docking. Depending on whether a vehicle’s motion dynamics is easy to obtain, there are model-based control methods and model-free control methods. Model-based approaches usually require less algorithm complexity and computational capabilities, but their performance can be jeopardized by uncertain factors such as actuator faults, model bias, and measurement errors. Although remarkable advances have been achieved in both directions, unsupervised autonomous vehicles are difficult for the public to fully accept, indicating the necessity of developing human-in-the-loop controllers.

2 Filtering for multisource data

Sensing modules are the eyes of vehicles, and various types of sensors have been attached to autonomous vehicles because of their distinguished abilities (Butt et al., 2022). Cameras are efficient and economical for classifying the texture of their surroundings. The development of event cameras has further conquered the issues of transmission latency and motion blur (Klenk et al., 2023). Radars are implemented for blind spot warning, collision avoidance, and adaptive cruise control, while Lidars can provide point cloud data that helps us construct three-dimensional models of the local environment. In addition, real-time kinematic positioning is proposed to offer centimeter-level precision for real-time localization.

However, each kind of sensor has its own shortcomings. For example, cameras need to work with proper brightness, and simultaneous localization and mapping are not dependable for Lidars due to their fatal cumulative error. To avoid the above issues, we can integrate the available sensors to achieve intersensor compensation. The solution in control engineering is Kalman filtering, where an optimal weighted average of noisy measurements and model-based predictions is achieved (Chui and Chen, 2017).

The original Kalman filter was first built for linear systems where both the measurement noise and process noise are uncorrelated white Gaussian noise sequences. To enhance the practicality of the algorithm, complex scenarios in which both noise sequences are correlated, both noise sequences are colored, and the system model is nonlinear are investigated. In addition, smoothers with dynamic windows are developed to perform dynamic optimization of our estimation. The Kalman filter is a

✉ Corresponding author.
E-mail: wangliang0117@tsinghua.edu.cn

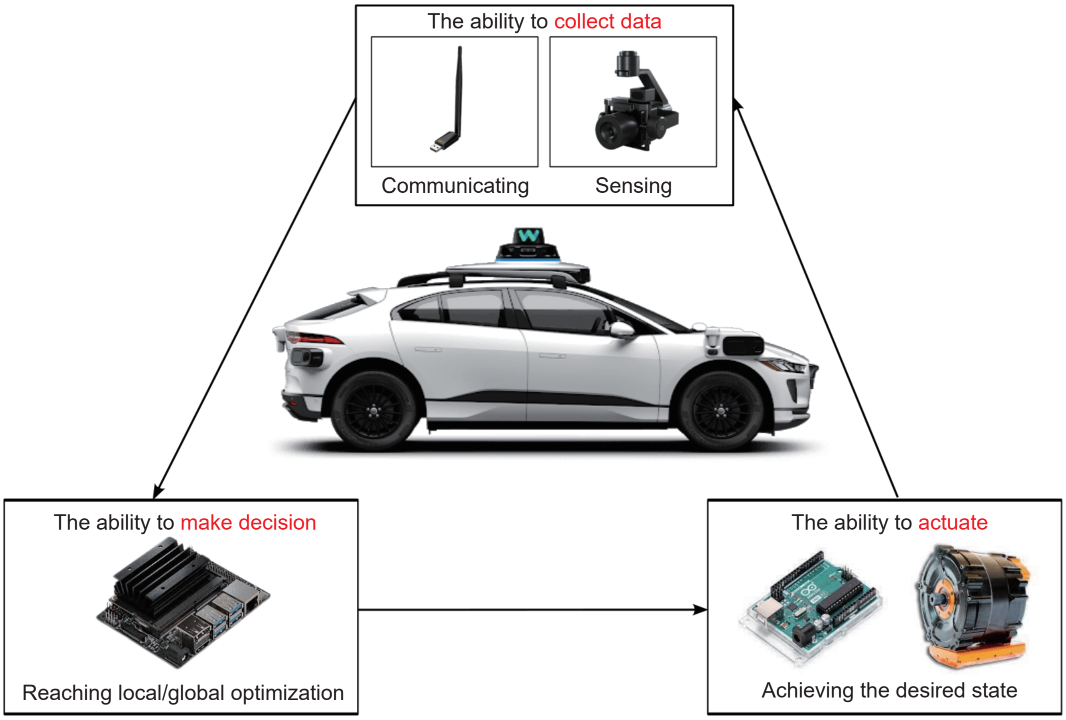


Fig. 1 Key features of an autonomous vehicle.

popular choice for state estimation and target tracking (Cao et al., 2023).

The current main focus of sensor fusion regarding the development of autonomous vehicles is achieving intersensor collaboration to integrate data with unique information. For example, Lidars cannot abstract colors (RGB values) from the environment, but cameras can. Therefore, combining these two types of sensors can lead to colored point clouds, which are helpful for the construction of three-dimensional models. However, few studies have discussed the optimal weighted average of data from different categories of sensors.

Specifically, if we employ both Lidars and cameras (without thermal modules) for an autonomous vehicle, can we always trust the outputs of cameras and Lidars equally regardless of weather conditions and brightness? Perhaps the answer is not because the precision of camera-based computer vision is compromised in dark environments, which is the reason why the autonomous driving feature is compulsorily terminated when lights are unavailable for Tesla products.

Therefore, we think that the upcoming challenge in terms of sensor fusion for autonomous vehicles is to develop an evaluation scheme that determines the trustworthiness of each sensor according to its characteristics and the current environment. This scheme should be able to achieve a dynamic and adaptive combination of sensor data, which can help us reconstruct a vehicle's local surroundings in different scenarios.

Case study 1: The core concept of the Kalman filter is to achieve an adaptive average of measurement outcomes and model-based prediction. The weight is correlated with the confidence level of different data resources, which is determined by the source's noise sequence's variance. A higher variance leads to a lower confidence level.

In terms of sensor fusion, we usually use environmental conditions to adjust the confidence rates. However, we only have sensor data from different sources without any model-based predictions. For instance, when overall brightness is compromised, the fusion algorithm should decrease the confidence rate of data from visible light cameras and increase the confidence rate of data from Lidars. In addition to the characteristics of measurement noise, factors such as the effective region, sample frequency, and resolution ratio should also be considered.

For direct illustration, an example is given in Fig. 2, where sensors with different characteristics are applied. Sensor 1 is less trustworthy with a noise variance of $Q_1 = 0.09$, while sensor 2 has $Q_2 = 0.04$. After implementing the Kalman filter technique, we are able to achieve a weighted average of data from both sources, which is represented in red. The fusion result has the lowest error variance and thus is more stable and more suitable for decision making, trajectory planning and motion control.

3 Robust and adaptive estimation of unknown factors

Compared to the problem of sensor fusion, the estimation of unknown states requires a different way of thinking because there are no available sensors. Therefore, we need to find the correlation between the measurable states and the unknown states, which requires partial knowledge of the actual system dynamics.

In control, we classify systems in accordance with the specific dynamics order if applicable, and first-order dynamics and second-order dynamics are usually sufficient for our analysis. However, high-order models are needed if we want to perform precise control of a system's jerk or snap, which cannot be measured. To overcome this issue, a structure called the extended state observer (ESO) is developed, where an additional state vector is defined to represent the unknown derivative of the state with the highest order (Hong et al., 2023). By correcting the states in each layer according to the difference between the virtual system and the physical system, system states with arbitrary orders can be approximated.

Although the ESO design can also estimate model uncertainties, such a method is problematic because it sometimes does not make full use of the available information. Hence, the uncertainty estimator is proposed to concentrate on model uncertainties and

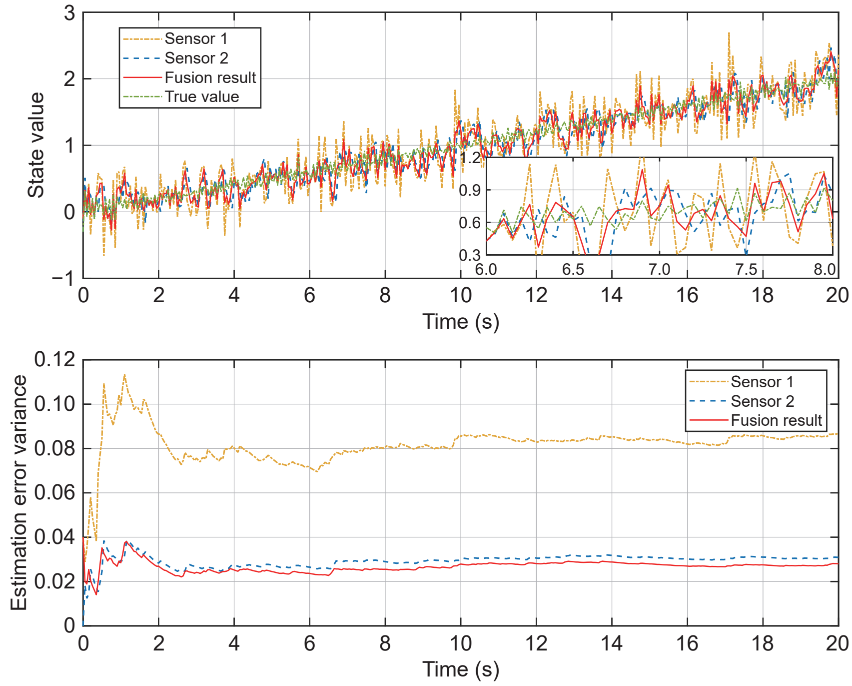


Fig. 2 Illustration of the effectiveness of sensor fusion.

external perturbations. When all system states are accessible, neural networks are embedded into the ESO structure to replace the extended state (Fei et al., 2022) to further obtain neural-based observers (NBOs). Sometimes, when the physical model is too complex to analyze, it is also acceptable to use one artificial neural network to represent the entire system model. Specifically, if the system state is $x \in R^n$, then the model estimator is constructed as $\dot{\hat{x}} = \widehat{W}T\left[\widehat{\phi}T(x)\right]$, where $\widehat{\phi}$ is the weight matrix of the hidden layer, $T(\cdot)$ is the activation function and $\widehat{W}$ is the weight matrix prior to network output.

In recent years, the concept of digital twins (DTs) has gained popularity in the field of intelligent vehicles and transportation. The concept was first introduced in 2011 to indicate a dynamic mapping from the physical world to the digital world. Specifically, one DT should have the following three characteristics: (1) possess identical dynamics as the physical system; (2) maintain consensus with the physical system through real-time data collection; and (3) provide information that can be used for the control of its physical twin. In short, a DT in engineering should be a virtual system that constantly maintains consensus with the physical system and provides helpful information for decision making and motion control (Botín-Sanabria et al., 2022). In particular, researchers believe that DTs have a promising future in the field of fault diagnosis and estimation (Classens et al., 2021).

However, how to construct, control, and visualize digital twins remains an open question for the engineering sector. In particular, for vehicles, in addition to observing uncertain factors regarding motion dynamics, DTs should also help us monitor components and hardware attached to vehicles and further provide us with recommendations for customized maintenance according to real-time estimations of vehicular health. Therefore, DTs have promising potential for advancing intelligent vehicles.

Case study 2: DTs have great potential for estimating actuator faults. For example, our goal is to control an omnidirectional robot (Fig. 3) subjected to a random actuator fault. To ensure the robustness of the proposed controller, it is necessary to diagnose the fault and how the fault affects system performance.

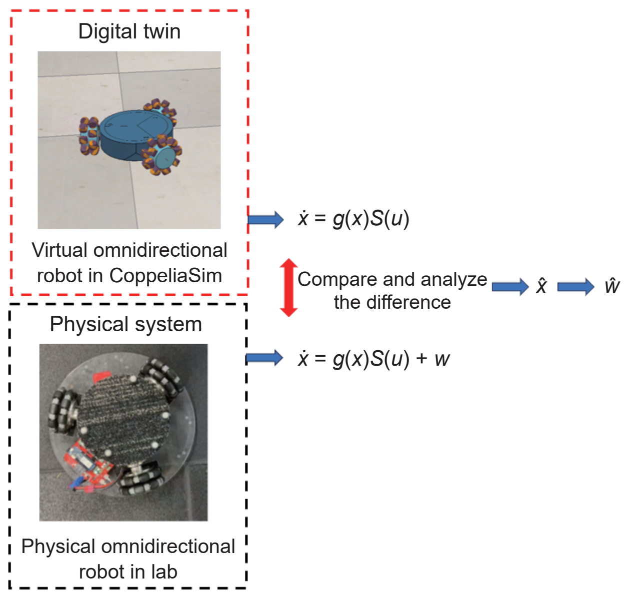


Fig. 3 DT's application in uncertainty estimation and compensation.

In theory, a DT is an identical copy of a physical system, meaning that the ideal state propagation laws are identical. By employing the same set of control laws, the digital robot and the physical robot will move simultaneously, yet the actuator fault will lead to $x - \widehat{x} \neq 0$. Then, we can implement adaptive algorithms to determine the value of $\widehat{w}$ that will result in $x - \widehat{x} \to 0$, and the system performance will be improved by compensating for the effect of $\widehat{w}$ in the control law. With proper design, if we define the difference between the actual fault and the estimated fault as $\widetilde{w} = w - \widehat{w}$, then the value of $\widetilde{w}$ should share similar trends as the purple curve in Fig. 4, where the estimation error of the DT-based finite-time approximation scheme converges within 3 s. The results indicate that DT-based estimation has a fast response and therefore can be applied to scenarios with demands on real-time characteristics.

https://doi.org/10.26599/JICV.2023.9210040

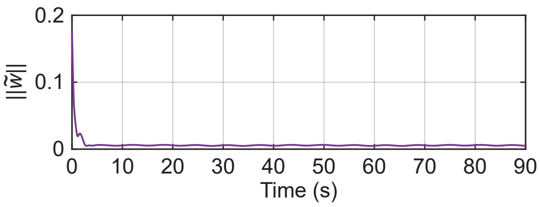


Fig. 4 Example of how the estimation error should propagate.

4 Event-triggered schemes for vehicles with limited communication bandwidth

Although breakthroughs have been achieved in the field of wireless communication to allow fast transmission of large volumes of data, it is unreasonable to model ICVs as agents with unlimited bandwidth due to the high number of vehicles in future transportation systems. In addition, periodic high-frequency communication is unnecessary when the data sent out are highly similar to those contained within the previous package. Therefore, the concept of event trigger communication was developed to minimize the communication burden without compromising system stability.

This technique was first implemented in a networked control structure to achieve aperiodic data transmission between sensors and controllers (Zhao et al., 2021). Suppose the real-time system state is $x \in R^n$ and the accessible triggered system state is $x(\tau_k) \in R^n$, where τ_k indicates the k-th event when the state is updated. Then, the core component of the event-triggered scheme is to analyze how much the measurement error of $E_x = x - x(\tau_k)$ affects our design. As the onboard computational power was enhanced, the networked control structure was then replaced by a multiagent structure (Dimarogonas et al., 2011). The stability analysis of the multiagent distributed trigger scheme is more complex because the trigger scheme only affects neighboring agents, meaning that an agent needs to evaluate how other agents affect itself if they operate with outdated data.

Afterwards, the static trigger scheme is found to be insufficient due to the high steady error, which indicates the demand of adaptively altering the trigger threshold according to the state of an agent. In other words, if the impact of the interagent communication error is relatively small, then we can have greater tolerance before the next interagent state update event, and vice versa. The above scheme is then summarized as the dynamic trigger scheme (Girard, 2014).

Although the issue of high steady-state error is solved by the dynamic trigger scheme, such a design requires the controller to perform real-time monitoring of the trigger thresholds, which may lead to burdens for the task scheduling process of embedded microcontrollers with limited computational power. Therefore, a new self-triggered algorithm was developed to estimate the expected arrival time of the upcoming task (Fan et al., 2015). However, the accuracy of the estimated arrival time varies from one system to another.

Although fruitful results have been obtained for event-triggered schemes for networked single agents and multiagent systems, most of them have focused only on motion control. This method lacks practicality because intervehicle cooperation is usually achieved in the decision-making or trajectory planning phase instead of low-level motion control.

In particular, many countries and regions are focusing on constructing the internet of vehicles to achieve optimal coordination of urban transportation networks, which requires a large-scale communication network among sensors, basic infrastructures, vehicles, and traffic control centers. Massive communication burden is expected for conventional time-triggered data transmission even if the 5G technique is employed due to the high number of nodes within the network. Hence, how to integrate event-triggered communication into collaborative decision making and trajectory planning are problems worthy of consideration for the development of ICVs.

Case study 3: The main idea of the event-triggered scheme is to reach a balance between tracking precision and communication cost without compromising system stability. This method mainly targets networked control systems and multiagent systems (Kang et al., 2023), and we choose a networked omnidirectional robot as our control object.

In the networked control structure, the controller relies on wireless communication to obtain measurements from sensors (Fei et al., 2023b). After applying the event-triggered mechanism, there will be a mismatch between the actual system state $x(t)$ and the triggered state $x(\tau_k)$ received by the controller. Hence, it is necessary to reach a balance between the measurement error E_x and the tracking error δ_x by defining the function $f(E_x, \delta_x) = f_1(E_x) - f_2(\delta_x)$, where $f_1(\cdot)$ and $f_2(\cdot)$ are both monotonically increasing functions. When $f(E_x, \delta_x) > \gamma > 0$ is satisfied, the measurement error is considered significant enough for an update.

When γ is a positive constant, the trigger scheme is classified as statically triggered. If γ is an adaptive term correlated with E_x, the scheme is categorized as dynamically triggered. By applying the dynamic trigger scheme, we obtain the results shown in Fig. 5. Without compromising the tracking precision, the dynamic triggering scheme prolongs the interevent time from 8 to approximately 110 ms. In terms of the application of ICVs, we can reduce unnecessary wireless communication events during traffic jams or when ICVs are working as expected.

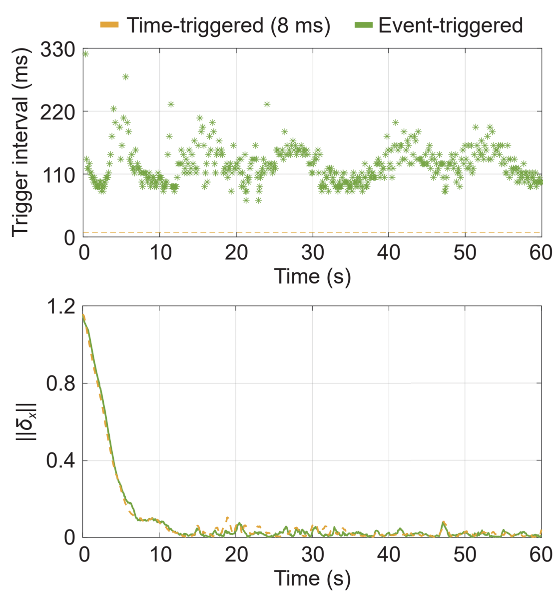


Fig. 5 Comparison of the event-triggered scheme and the time-triggered scheme.

5 Robust motion controller for vehicles

There are two main categories of low-level motion control: model-based approaches and model-free approaches (Xu and Peng, 2019). It is quite straightforward that model-based approaches require prior knowledge of the system's dynamics, such as the order of dynamics, discrete-time, or continuous-time, and the form of a control gain matrix, while model-free approaches do not.

First, the most commonly known proportional-integral-derivative (PID) control can be either model-based or model-free depending on how the parameter values of *P*, *I*, and *D* are chosen. For instance, if the optimal parameter values are obtained by solving linear matrix inequalities that are determined by the specific system model, then the algorithm is model-based. In contrast, if you decide to tune the parameter values solely according to the system output, your method is model-free.

Model-based approaches are widely used for industrial purposes due to their low demand for computational power and low storage capability. Well-known examples include active disturbance rejection control, backstepping control, feedback linearization control, H-infinity control, sliding mode control, and model predictive control (MPC). Among them, MPC is the most popular due to its implementation of a receding horizon for rolling optimization (Mayne et al., 2000). To date, MPC has demonstrated great advantages in the control of nonlinear systems with various constraints, including quadcopters and legged robotics.

On the other hand, model-free approaches require no prior knowledge of the system, meaning that we treat the actual system dynamics as a black box by setting $\dot{x} = f(x, t)$. Therefore, each model-free algorithm has a distinctive module for model estimation, and the major difference is how to perform model estimation. Methods such as data-driven control (Hou and Wang, 2013), dynamic programming control (Liu et al., 2020), and adaptive neural-based control (Fei et al., 2023a) choose to perform online system model approximation, meaning that the estimated system model changes along with real-time feedback. However, some researchers tend to complete system identification offline with datasets and employ fixed models for control.

Regardless of the specific control structure, it is almost impossible to guarantee a success rate of one hundred percent for all practical scenarios, leading to a lack of trust in the public. Therefore, although autonomous vehicles have been implemented in closed areas such as ports and mines, we believe that the close future for intelligent vehicles is to develop computer-aided driving technologies, which involves the investigation of human-in-the-loop systems. As a result, control algorithms need to be modified to be sensitive to human factors to further achieve personalized optimal driving experiences for ICVs.

Case study 4: Before applying one specific control technique, it is essential for us to understand its merits and shortcomings. First, we will offer a comparative analysis of the model-based approaches and the model-free approaches.

Model-based approaches:

(1) Merits: This approach has lower demand for onboard computational power and makes full use of prior model knowledge.

(2) Drawbacks: These drawbacks cannot be applied to systems that are too complex to model; they are less robust when the system is subjected to unmodeled uncertain factors.

Model-free approaches:

(1) Merits can be applied to every plant, can be applied for system identification, and possess high robustness.

(2) Drawbacks: This requires a dataset for offline training, which can easily lead to state oscillation at the beginning of online training.

Therefore, combining model-based techniques with model-free techniques can result in a model-adaptive scheme, which further leads to intermethod compensation. For example, we can employ neural networks to estimate modeling errors by treating system states as network inputs and implementing observers to adaptively track external disturbances (stochastic wind, uneven ground, etc.). To offer a direct illustration, a comparative study regarding the trajectory tracking control of a networked omnidirectional robot is provided in Fig. 6.

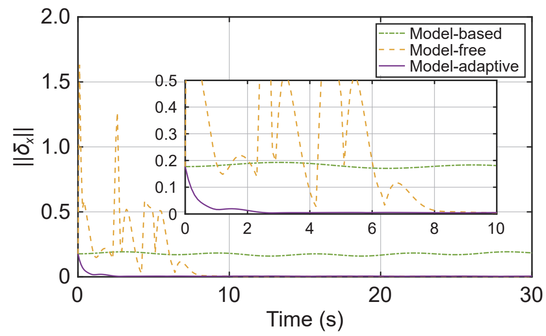


Fig. 6 Comparison of three control structures (δ_x is the state tracking error).

Because of model uncertainties, the model-based approach has a significant constant error that satisfies $\delta_x \le 0.2$, indicating low robustness. Although the tracking error of the model-free method achieves ultimate convergence, the system experiences remarkable state oscillation in the first 8 s. In comparison, the model-adaptive scheme has the least amount of state chattering, the fastest convergence speed, and the highest estimation precision. Therefore, model-adaptive methods are more suitable for industrial scenarios.

In addition to system robustness, optimality is also an important factor. Apart from examining the optimality of the current decision or control command, it is also essential to look into the future. The method of MPC is developed by constantly predicting system performance through a dynamic time window that includes the next several seconds or time steps (Fig. 7). Model predictive control is now widely employed in trajectory planning modules and motion control modules for ICVs. By combining adaptive control theory and model predictive control theory, ICVs can simultaneously possess robustness, optimality and safety.

6 Conclusions

This paper aims to provide a brief introduction of the state-of-the-art control techniques for sensing, communication and control and offers insights into how they can change the future of autonomous and connected vehicles. Specifically, the Kalman filtering method offers a potential direction for achieving the optimal weighted average among sensors. Observers and estimators can offer insights for developing digital twins, event-triggered mechanisms can be embedded into high-level collaborative operations within multivehicle systems, and human-in-the-loop control algorithms are needed for computer-aided intelligent driving. In summary, control engineering not only plays a critical role in the development of autonomous and connected vehicles but also points out promising directions for future development and research.

Acknowledgements

This work was supported by the National Key R&D Program of China (2023YFB4301800), the National Natural Science

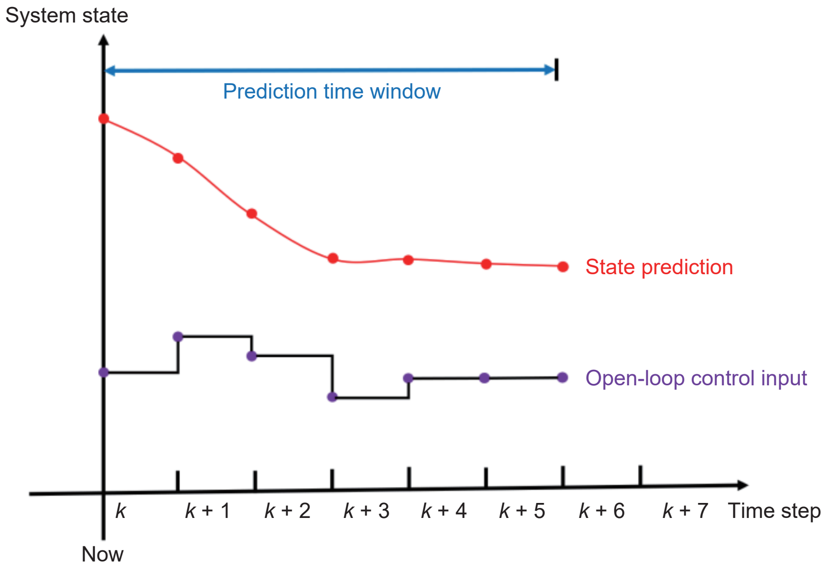


Fig. 7 Illustration of model predictive control.

Foundation of China (52221005 and 52220105001), and the Shui-Mu Scholar Program of Tsinghua University, China.

Declaration of competing interest

The authors have no competing interests to declare that are relevant to the content of this article. The authors Yang Liu and Liang Wang are the Editorial Committee members of this journal.

References

Butt, F. A., Chattha, J. N., Ahmad, J., Zia, M. U., Rizwan, M., Naqvi, I. H., 2022. On the integration of enabling wireless technologies and sensor fusion for next-generation connected and autonomous vehicles. IEEE Access, 10, 14643–14668.

Botín-Sanabria, D. M., Mihaita, A. S., Peimbert-García, R. E., Ramírez-Moreno, M. A., Ramírez-Mendoza, R. A., de J Lozoya-Santos, J., 2022. Digital twin technology challenges and applications: A comprehensive review. Remote Sens, 14, 1335.

Cao, X., Ren, L., Sun, C., 2023. Dynamic target tracking control of autonomous underwater vehicle based on trajectory prediction. IEEE Trans Cybern, 53, 1968–1981.

Chui, C. K., Chen, G., 2017. *Kalman Filtering*. Berlin, DE: Springer International Publishing.

Classens, K., Heemels, W. P. M. H. M., Oomen, T., 2021. Digital twins in mechatronics: From model-based control to predictive maintenance. In: 2021 IEEE 1st International Conference on Digital Twins and Parallel Intelligence (DTPI), 336–339.

Dimarogonas, D. V., Frazzoli, E., Johansson, K. H., 2011. Distributed event-triggered control for multi-agent systems. IEEE Trans Automat Contr, 57, 1291–1297.

Fan, Y., Liu, L., Feng, G., Wang, Y., 2015. Self-triggered consensus for multi-agent systems with zeno-free triggers. IEEE Trans Automat Contr, 60, 2779–2784.

Fei, Y., Shi, P., Lim, C. C., 2022. Neural-based formation control of uncertain multi-agent systems with actuator saturation. Nonlinear Dyn, 108, 3693–3709.

Fei, Y., Shi, P., Lim, C. C., 2023a. Robust and collision-free formation control of multiagent systems with limited information. IEEE Trans Neural Netw Learning Syst, 34, 4286–4295.

Fei, Y., Zhang, D., Sun, Y., Shi, P., 2023b. Dynamically triggered estimator-based controller and its application on an omnidirectional robot. IEEE Trans Automat Sci Eng, 1–12.

Girard, A., 2014. Dynamic triggering mechanisms for event-triggered control. IEEE Trans Automat Contr, 60, 1992–1997.

Hou, Z. S., Wang, Z., 2013. From model-based control to data-driven control: Survey, classification and perspective. Inf Sci Int J, 235, 3–35.

Hong, M., Gu, X., Liu, L., Guo, Y., 2023. Finite time extended state observer based nonsingular fast terminal sliding mode control of flexible-joint manipulators with unknown disturbance. J Frankl Inst, 360, 18–37.

Kang, Y., Luo, D., Xin, B., Cheng, J., Yang, T., Zhou, S., 2023. Robust leaderless time-varying formation control for nonlinear unmanned aerial vehicle swarm system with communication delays. IEEE Trans Cybern, 53, 5692–5705.

Klenk, S., Koestler, L., Scaramuzza, D., Cremers, D., 2023. E-NeRF: Neural radiance fields from a moving event camera. IEEE Robot Autom Lett, 8, 1587–1594.

Liu, D., Xue, S., Zhao, B., Luo, B., Wei, Q., 2020. Adaptive dynamic programming for control: A survey and recent advances. IEEE Trans Syst Man Cybern, Syst, 51, 142–160.

Mayne, D. Q., Rawlings, J. B., Rao, C. V., Scokaert, P. O. M., 2000. Constrained model predictive control: Stability and optimality. Automatica, 36, 789–814.

Sun, Q., Wang, X., Yang, G., Chen, Y. H., Ma, F., 2023. Adaptive robust formation control of connected and autonomous vehicle swarm system based on constraint following. IEEE Trans Cybern, 53, 4189–4203.

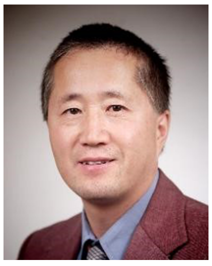
Xu, S., Peng, H., 2019. Design, analysis, and experiments of preview path tracking control for autonomous vehicles. IEEE Trans Intell Transport Syst, 21, 48–58.

Zhang, H., Liu, J., Wang, Z., Huang, C., Yan, H., 2023a. Adaptive switched control for connected vehicle platoon with unknown input delays. IEEE Trans Cybern, 53, 1511–1521.

Zhang, Y., Liang, X., Li, D., Ge, S. S., Gao, B., Chen, H., et al., 2023b. Adaptive safe reinforcement learning with full-state constraints and constrained adaptation for autonomous vehicles. IEEE Trans Cybern, 54, 1907–1920.

Zhao, N., Shi, P., Xing, W., Chambers, J., 2021. Observer-based event-triggered approach for stochastic networked control systems under denial of service attacks. IEEE Trans Control Netw Syst, 8, 158–167.

Yang Fei received the B.Eng. degree in control science and engineering from Harbin Institute of Technology, China, in 2018; and the Ph.D. degree in electrical and electronic engineering as the valedictorian along with a Dean’s Commendation for Doctoral Thesis Excellence from the University of Adelaide, Australia, in 2022. He is now a Shui-Mu post-doctoral research fellow with the Emerging Transportation Solution Lab, School of Vehicle and Mobility, Tsinghua University, China. His current research interests include multi-agent systems, neural network adaptive control, intelligent transportation systems, robotics, and drone-based delivery.



Peng Shi received the Ph.D. degree in electrical engineering from the University of Newcastle, Australia, in 1994 and the Ph.D. degree in mathematics from the University of South Australia in 1998. He was awarded the Doctor of Science degree from the University of Glamorgan, Wales, in 2006 and the Doctor of Engineering degree from the University of Adelaide, Australia, in 2015. He is now a Professor at the University of Adelaide, Australia. His research interests include systems and control theory and applications to autonomous and robotic systems, network systems and cyber-physical systems. He now serves as the Editor-in-Chief of *IEEE Transactions on Cybernetics*, the Senior Editor of *IEEE Access*, the Distinguished Lecturer of IEEE SMC Society, and the President of the International Academy for Systems and Cybernetic Science. He is a Fellow of IET, IEAust, and CAA and a Member of the Academy of Europe.

Yang Liu received the Ph.D. degree at Southeast University, China, in 2021. Currently, he is a Marie Curie Fellow at the Department of Architecture and Civil Engineering, Chalmers University of Technology, Sweden, and a Visiting Scholar at the School of Vehicle and Mobility, Tsinghua University, China. His research interests include intelligent transportation systems, AI techniques, and data mining, with applications in complex real-world problems such as autonomous vehicles and urban mobility. He serves as a Young Editor for two top-tier academic journals, *The Innovation* and *IEEE/CAA Journal of Automatica Sinica*. In addition, he is an Associate Editor of *IEEE Transactions on Intelligent Vehicles* and *Journal of Intelligent and Connected Vehicles.*

Liang Wang received the B.Eng. and M.Eng. degrees from Tsinghua University, Beijing, China, in 2006 and 2009, respectively; and the Ph.D. degree from Columbia University, USA, in 2016. He is currently an Assistant Research Professor with the School of Vehicle and Mobility at Tsinghua University, China. His research interests include transportation digital-twin technology, building information modeling, ground-air cooperation, and UAV applications. Additionally, he serves as the Associate Editor of *Journal of Intelligent and Connected Vehicles.*