Guest Editorial to the Special Section on Composite Adaptive and Learning Control With Robotic Applications

COMPOSITE adaptive control integrates direct and indirect adaptive control to achieve asymptotic convergence of both tracking errors and prediction errors while maintaining the global stability of the closed-loop system [1]. To explain the smooth behavior of parameter estimation in composite adaptation, it is convenient to interpret the composite adaptive law as passing through a time-varying low-pass filter, where the parameter search goes along an averaging direction specified by the low-frequency components of the tracking error. The advantages of composite adaptation come from two aspects: 1) The prediction error that contains the implicit information of parameter estimation errors provides an extra contribution to the convergence of estimation and control; 2) owing to the averaging effect, higher adaptation gains can be specified to achieve faster convergence without exciting high-frequency unmodeled dynamics. The superiority of composite adaptive control has been verified in many real-world robotic systems. Nevertheless, without a condition of persistent excitation (PE), the averaging effect is invalid, and parameter convergence still cannot be ensured in composite adaptation. The PE condition requires the persistent richness of closed-loop signals, which is too stringent to be satisfied in practice. Even if some level of excitation occurs, the rate of parameter convergence highly depends on the excitation strength, generally resulting in slow parameter convergence.

Learning is one of the key features of autonomous intelligent behavior, which is reflected by parameter convergence in adaptive control and estimation [2]. In recent years, many efforts have been made to achieve parameter convergence with relaxed PE by making use of data memory. Motivated by composite adaptation, composite learning has been proposed to achieve parameter convergence in adaptive systems under interval excitation (IE), a condition strictly weaker than PE, where parameter convergence is proven to be exponential, and the rate can be made arbitrarily high by increasing an adaptation gain [3]. Composite learning applies regressor extension with online data memory to composite adaptation, which relaxes the stringent requirements on persistent data richness and long learning duration for parameter estimation. Exponential parameter convergence provides significant advantages such as accurate online identification, superior trajectory tracking, and robust adaptation without parameter drift.

Composite learning can be regarded as a natural evolution of composite adaptation to the learning framework and has been successfully applied to trajectory tracking, interaction control, and visual servoing of many real-world robotic systems such as industrial robots, collaborative robots, robots with compliant actuators, and hydraulically driven robots [4]. Compared with composite adaptation and other parameter learning schemes, composite learning exhibits several distinctive features: 1) It can naturally handle slowly time-varying or suddenly changing (but piecewise constant) parameters; 2) it still works if only partial IE exists; 3) it does not need numerical differentiation, making it more robust to measurement noise; 4) it does not require extra computing costs resulting from, e.g., singular value maximization and state derivative estimation.

This special section devotes to tighten the bond between the theory of composite adaptation and learning and its robotic applications. The first article [A1] provides a comprehensive overview of four data memory-driven parameter estimation schemes (one of them being composite learning) for adaptive systems under a historical perspective and highlights the distinctive features of composite learning in terms of computational simplicity, estimation accuracy, robustness against perturbations, and widespread real-world applications to robot learning and control. It also provides visions for future research and development in the relevant topic. The rest of the articles collected are classified into two groups as follows.

The first group of the articles addresses demands and challenges for integrating composite adaptation and learning with other control structures. In [A2], an enhanced adaptive optimal control method is proposed for robotic systems to achieve constraint satisfaction of joint positions and velocities under model uncertainties, where composite learning is applied to reduce the conservatism of control barrier functions designed by tightening the bounds of unknown parameters. Simulations on a robot model with two degrees of freedom (DoFs) illustrate the effectiveness of the proposed method. In [A3], a physics-informed data-driven control method is designed for discrete-time linear systems, where the control design starts from a robust controller using physics information when no data sample is available and progressively evolves towards a

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fully adaptive controller as more data become available, which enhances the feasibility of safe control and the performance of optimal control. Two simulation applications are available in this article, including the safe hovering of a quadcopter and the quadratic regulation of a Lithium-ion battery. The method in [3] provides a promising framework for combining composite adaptation and learning to achieve data-driven safe optimal control. In [4], an iterative learning embedded composite adaptive visual servoing method is proposed to overcome the control challenges of in-situ off-axis rotation in nanorobots under model uncertainties and visual disturbances. Compared to [A2], [A3], [A4] provides extra experiments to demonstrate that the proposed method can realize high-precision rotation under average accuracy within several microns.

The second group of the articles concentrates on application-oriented research to solve specific robot control problems. In [A5], a composite learning robot control method is proposed to address the task-space tracking problem under kinematic and dynamic uncertainties. Simulations on a 2-DoF robot model exhibit the effectiveness of the proposed method. In [A6], a concurrent learning adaptive longitudinal platooning method is developed for autonomous vehicles under unknown powertrain parameters. Concurrent learning can be regarded as a discrete-data version of composite learning, where a finite set of online data is exploited to enhance parameter convergence. Simulations of a platoon with five vehicles verify the theoretical analysis. In [A7], a distributed composite learning control method is proposed for mobile sensor networks, where the information exchange between agents is leveraged collectively to achieve parameter convergence. Experiments with multiple drones verify the efficacy of the proposed concept. In [A8], an image-based composite learning visual servoing method is proposed for redundant robots under an eye-to-hand monocular camera with unknown parameters. The proposed method considers the robot dynamics in the Cartesian space and exploits the kinematic redundancy of robots, where impedance control is applied in the nullspace of the visual task to avoid damaging robot interaction. Experiments on a 7-DoF robot arm validate that the proposed method performs well on parameter estimation, visual regulation, and compliant interaction.

Appendix: Related Articles

[A1] Y. Pan and T. Shi, "Adaptive estimation and control with online data memory: A historical perspective," *IEEE Control Syst. Lett.*, vol. 8, pp. 267–278, 2024, doi: 10.1109/LCSYS.2024.3364588.

[A2] D. Zeng, Y. Jiang, Y. Wang, H. Zhang, and Y. Feng, "Robust adaptive control barrier functions for input-affine systems: Application to uncertain manipulator safety constraints," *IEEE Control Syst. Lett.*, vol. 8, pp. 279–284, 2024, doi: 10.1109/LCSYS.2023.3329518.

[A3] N. Niknejad and H. Modares, "Physics-informed data-driven safe and optimal control design," *IEEE Control Syst. Lett.*, vol. 8, pp. 285–290, 2024, doi: 10.1109/LCSYS.2023.3333257.

[A4] H. Zhang, X. Fu, S. Liu, and Y. Wang, "Iterative learning embedded composite model reference adaptive control for off-axis in-situ rotation in nanorobotic manipulation," *IEEE Control Syst. Lett.*, vol. 8, pp. 291–296, 2024, doi: 10.1109/LCSYS.2023.3336545.

[A5] Z. Zhang, K. Guo, and Y. Pan, "Composite learning exponential tracking robot control with uncertain kinematics and dynamics," *IEEE Control Syst. Lett.*, vol. 8, pp. 297–302, 2024, doi: 10.1109/LCSYS.2023.3344675.

[A6] Q. Wen, D. Liu, J. Wang, and S. Baldi, "An adaptive longitudinal platooning design based on concurrent learning," *IEEE Control Syst. Lett.*, vol. 8, pp. 303–308, 2024, doi: 10.1109/LCSYS.2023.3333004.

[A7] S. Surendhar, S. B. Roy, and S. Bhasin, "Collective initial excitation based distributed composite adaptive coverage control with application to a network of drones," *IEEE Control Syst. Lett.*, vol. 8, pp. 309–314, 2024, doi: 10.1109/LCSYS.2023.3335957.

[A8] Z. Li, W. Li, and Y. Pan, "Composite learning image-based visual servoing of redundant robots with nullspace compliance," *IEEE Control Syst. Lett.*, vol. 8, pp. 315–320, 2024, doi: 10.1109/LCSYS.2024.3351559.

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[1] J.-J. E. Slotine and W. Li., "Composite adaptive control of robot manipulators," *Automatica*, vol. 25, no. 4, pp. 509–519, Jul. 1989.

[2] P. J. Antsaklis, "Intelligent learning control," *IEEE Control Syst. Mag.*, vol. 15, no. 3, pp. 5–7, Jun. 1995.

[3] Y. Pan and H. Yu, "Composite learning from adaptive dynamic surface control," *IEEE Trans. Autom. Control*, vol. 61, no. 9, pp. 2603–2609, Sep. 2016.

[4] K. Guo and Y. Pan, "Composite adaptation and learning for robot control: A survey," *Annu. Rev. Control*, vol. 55, pp. 279–290, Dec. 2023.

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