Learning and Predicting Uncertainties for Robotic Control and Planning

Figure 1: An overview of my Ph.D. research

Background. Robots deployed in the real world inevitably face uncertainties caused by internal model mismatch and external unmeasured disturbances. With the vision of general intelligent systems, it becomes mandatory to enable robots to operate in unknown dynamic environments. Improving environmental adaptability, however, poses enormous challenges for robots, necessitating the ability to precisely recognize and quantify uncertainties from limited measurements and computing resources.

Ph.D. research. The topic of my Ph.D. research is learning and predicting uncertainties for robotic control and planning, as shown in Fig.1. Two key challenges exist to achieve this purpose: how to recognize the uncertainty and how to handle the uncertainty. 1) For the first challenge, I followed the research route from analytically deep-coupling modeling to data-based learning. The proposed uncertainty estimation algorithms must satisfy precision, lightweight, universality, and stability. Especially, by combining the traditional control and advanced learning schemes, two uncertainty estimation schemes, named FORESEER[1] and EVOLVER[2], are developed. Extensive experiments on various platforms have been conducted to demonstrate their effectiveness. 2) For the second challenge, apart from the feedforward compensation strategy for the estimated uncertainty, that existing works usually adopted, I developed several uncertainty utilization schemes. In the upper planning level, the estimated wind disturbance can be utilized to enlarge the acceleration constraint so that an energy-saving and time-saving trajectory can be obtained[1]. In lower control level, the drag disturbance is shown to be beneficial to improve the control accuracy[4].

Future work. Recent years have witnessed a rapid development of data-driven learning (e.g., RNN, CNN, Transformer), fueled by the availability of vast amounts of data and the advancement of updated learning. Especially, within the RL framework, the deep learning strategy has been employed in various robotic platforms, including aerial, quadruped, and humanoid robots. However, current neural algorithms are still some away from the underlying mechanism of human brains. For example, neural circuits in brains are much more robust to uncertainties than artificial neural networks. To address the well-known generalization problem, plenty of algorithms including domain randomization, few-shot learning, one-shot learning, meta-learning, imperative learning, and liquid neural network are being studied in full swing.

I want to solve this problem by combining feedback-based control and data-driven learning, instead of only just one of them. I believe there is a harmonious solution to merge active learning with reactive control in organisms. For example, for the optomotor control of the larval zebrafish, an abrupt uncertainty can be attenuated promptly by the reactive control for initial safety. The learning mechanism is meanwhile triggered to exploit the uncertainty model. The learned model is lastly utilized in the reactive control with a prominent performance improvement. **My next purpose is to establish a harmonious, hierarchical, and biomimetic framework that can properly integrate prior knowledge** (obtained by modeling or offline learning), **online learning, and feedback control.** After being embedded with this framework, the robot's ability to adapt to unknown environments will be greatly enhanced.

Research publication:

(Equal contributions)*

[1] **Jia, J.**, Guo, K., Wang, Y., Zhou, S., Zhang, J., Liu, Y., Yu, X., Shi, Y., Guo, L. (2024). FORESEER: Recognize and utilize uncertainties by integrating data-based learning and symbolic feedback. ***under review***. [Video]

[2] **Jia, J.**, Zhang, W., Guo, K., Wang, J., Yu, X., Shi, Y., & Guo, L. (2024). EVOLVER: Online learning and prediction of disturbances for robot control. ***IEEE Transactions on Robotics***, 40, 382–402. [Video]

[3] **Jia, J.**, Guo, K., Yu, X., Guo, L., & Xie, L. (2022). Agile flight control under multiple disturbances for quadrotor: Algorithms and evaluation. ***IEEE Transactions on Aerospace and Electronic Systems***, 58(4), 3049–3062. [Video]

[4] **Jia, J.**, Guo, K., Yu, X., Zhao, W., & Guo, L. (2022). Accurate high-maneuvering trajectory tracking for quadrotors: A drag utilization method. ***IEEE Robotics and Automation Letters***, 7(3), 6966–6973. [Video]

[5] **Jia, J.**, Liu, Y., Guo, K., Yu, X., Xie, L., & Guo, L. (2024). Disturbance observer for estimating coupled disturbances. ***arXiv***.

[6] Guo, K.∗, **Jia, J.*,** Yu, X., Guo, L., & Xie, L. (2020). Multiple observers based anti-disturbance control for a quadrotor UAV against payload and wind disturbances. ***Control Engineering Practice***, 102, 104560. [Video]

[7] **Jia, J.**, Guo, K., Wang, C., Shen, N., Jia, W., & Yu, X. (2022). Flight control for quadrotor safety in the presence of cog shift and loss of motor efficiency. ***In 2022 International Conference on Unmanned Aircraft Systems*** *(ICUAS)* (pp. 245–254). [Video]

[8] Guo, K.∗, **Jia, J. ***, Yu, X., & Guo, L. (2019). Dual-disturbance observers-based control of UAV subject to internal and external disturbances. ***In 2019 Chinese Automation Congress*** *(CAC)* (pp. 2683–2688). **Best paper**. [Video]

[9] Yang, Z., **Jia, J.**, Liu, Y., Guo, K ., Yu, X. (2024). TRACE: Trajectory refinement with control error enables safe and accurate maneuvers. ***In 2024 International Conference on Control & Automation*** *(ICCA)*. **Best student paper**. [Video]

[10] Zhang, W., **Jia, J.**, Zhou, S., Guo, K., Yu, X., & Zhang, Y. (2022). A safety planning and control architecture applied to a quadrotor autopilot. ***IEEE Robotics and Automation Letters***, 8(2), 680–687. [Video]

[11] Guo, K., Zhang, W., Zhu, Y., **Jia, J.**, Yu, X., & Zhang, Y. (2022). Safety control for quadrotor UAV against ground effect and blade damage. ***IEEE Transactions on Industrial Electronics***, 69(12), 13373–13383. [Video]