Transferring Learned Robot Skills via Federated Reinforcement Learning

Khalil Abuibaid[1], Vinit Hegeiste[1], Nigora Gafur[1], Tatjana Legler[1], Achim Wagner[2] and Martin Ruskowski[1,2]

***Abstract*— In this paper, we propose a concept used federated reinforcement learning (FRL) framework designed to facilitate the transfer of learned robot skills, such as peg-in-hole insertion tasks. This framework enables new robots to acquire task-specific skills through a shared global model while maintaining the privacy of their sensors and environmental data. We introduce a novel FRL framework to overcome the challenges associated with skill transfer in robotic systems.**

I. INTRODUCTION

Automation technology is undergoing a transformative evolution, propelled by the integration of artificial intelligence (AI) to increase efficiency, reliability, and adaptability in robotic applications [1]. Among the key advancements, reinforcement learning (RL) has become a foundation, empowering robots to explore and interact with their environments for optimal decision-making. As illustrated in Figure 1, RL enables robots to learn interaction skills, such as force and motion control, enhancing adaptability in dynamic settings. Concurrently, federated learning (FL) is redefining collaborative learning paradigms by facilitating decentralized learning across distributed systems. This approach eliminates the need to centralize raw data, ensuring data privacy and scalability [4].

FL offers a promising solution to uphold privacy while enhancing collaboration between partners. Recent studies [4], [5] highlight how FL accelerates innovation and efficiency by enabling distributed learning without compromising sensitive data in variant applications, which is critical advancement for modern industrial environments. [6] show that FL can manage the heterogeneity in shared production environments. However, FRL combines the strengths of RL and FL, creating a framework where distributed data enhances learning models without data centralization. As detailed in the work [3], FRL not only improves robustness but also reduces training times, making it a sustainable as transformative tool for complex robotic tasks. Applications of FRL span diverse domains, including mobile and serial robotics, as demonstrated in [7]–[11]. These innovations are driving intelligent automation systems toward greater adaptability and efficiency.

[1] The authors are with the Chair of Machine Tools and Control Systems, Department of Mechanical and Process Engineering, RPTU in Kaiserslautern, Kaiserslautern D-67663, Germany khalil.abuibaid@rptu.de

[2] The authors are with the German Research Center for Artificial Intelligence (DFKI), Kaiserslautern D-67663, Germany martin.ruskowski@dfki.de

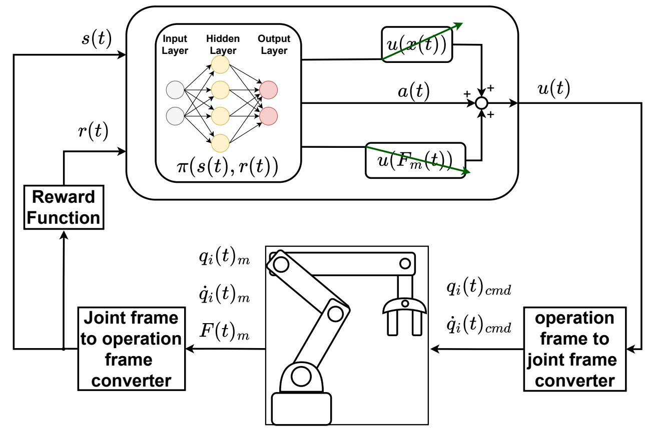

Fig. 1. The RL diagram shows the learning process of robot interaction skills with force and motion control which are denoted as $u(F_m(t)$ and $u(x(t))$ respectively .

Transferring skills in robotics remains a significant challenge, particularly in ensuring precision and adaptability in dynamic environments for different robots. Large interaction with environment along with prolonged training times further complicate the process. Recent advancements leverage global pre-trained models from natural language processing (NLP) and vision systems [2]. These models serve as backbones for numerous applications, enabling the reuse of standardized datasets across multiple robots, tasks, and environments, thus circumventing the need for task-specific training.

II. METHODOLOGY

We propose a decentralized approach applying FRL method, where each robot acts as an individual client in the FRL system, depicted in 2. The global model while aggregating its local models can achieve seamless collaboration between robot tasks, regardless of varying dynamic and kinematic configurations. However, when more clients join the FRL system, it can adapt the increased computational loads without performance degradation. This scalability is vital for industrial scenarios where numerous robots operate together, enabling real-time learning and adaptation. As shown in Figure 1, the RL policy governs the motion trajectory as well as the parameters of the force and motion controllers. The position control command is defined as follows

$$u(t) = a(t) + S(K_p^x x_e + K_d^x \dot{x}_e) + (I - S)(K_p^f F_e + K_i^f \int F_e dt), \quad (1)$$

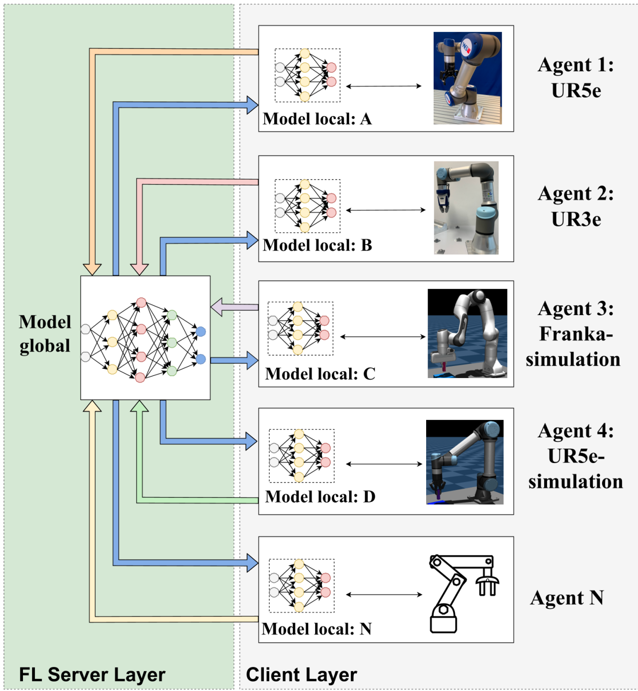

Fig. 2. Illustration of the FRL framework for sharing and transferring robotic skills across distributed systems.

where $a(t)$ denotes to the policy position action, $u(t)$ refers to the control command while the parameters $[K_p^x, K_d^x, K_p^f, K_i^f]$ represent the gains for the PD and PI controllers [14]. The term S is a selection matrix that determines the direction in Cartesian space in which either position or force control can respond [13]. The total reward function is defined as

$$r(t) = r_{sparse}(t) + r_{dense}(t). \quad (2)$$

The first term of the reward function (long-term reward) is formulated as

$$r_{sparse}(t) = \begin{cases} 100 & \textbf{Task completed} \\ -5 & \textbf{collision occurance} \\ -5 & \textbf{reaching max. num of steps} \end{cases} \quad (3)$$

and the $r_{dense}(t)$ (short-time reward) is computed as the summation of the position error distance and the force error relative to the defined goal, i.e. $\alpha_1 \|x_g - x_m\|_2 + \alpha_2 \|F_g - F_m\|_2$, where $\|.\|_2$ denotes to the Euclidean norm and each of reward component is weighted via α_i. At each episode, the total reward is designed to balance short-term feedback with long-term outcomes, whether the task is successfully completed or not.

III. Proposal

The idea is to demonstrate the FRL on a simulated benchmark task using MuJoCo [12]. The experiment will involve two robots, UR5e and Franka Emika Panda, performing a peg-in-hole insertion task. These robots differ in their kinematics and dynamics configuration. The proposed demonstration will help us to evaluate the collaborative learning, where robots refine hybrid force and motion control through a shared FRL model, leveraging collective experience while maintaining data privacy. This decentralized learning approach will not only allow each robot to efficiently acquire the necessary skills but also ensure that new robots joining later can immediately access and build upon the latest learned policy. The experiment can be further extended by integrating a real UR5e into the FRL structure, demonstrating its capability to efficiently transfer robotic skills for real-world applications.

IV. Conclusion

This work proposes a FRL framework to enhance robotic skill acquisition by integrating RL and FL. The approach aims to address challenges in skill transfer, training efficiency, and policy generalization across robots with different kinematic and dynamic configurations while preserving data privacy. To evaluate this concept, we propose a simulated peg-in-hole insertion task involving UR5e and Franka Emika Panda robots, with potential future extensions to real-world applications. If successful, FRL could enable scalable, decentralized robotic learning, paving the way for more efficient and adaptable automation in Industry 4.0. Future work will focus on optimizing computational efficiency, expanding task scope, and validating the framework in real-world deployments.

V. Acknowledgements

This work was funded by the Carl Zeiss Stiftung, Germany under the Sustainable Embedded AI project (P2021-02-009).

References

[1] Richard S. Sutton and Andrew G. Barto. 2018. Reinforcement Learning: An Introduction. A Bradford Book, Cambridge, MA, USA.

[2] O'Neill, Abby, et al. "Open x-embodiment: Robotic learning datasets and rt-x models: Open x-embodiment collaboration 0." 2024 IEEE International Conference on Robotics and Automation (ICRA). IEEE, 2024.

[3] Qi, Jiaju; Zhou, Qihao; Lei, Lei; Zheng, Kan (2021): Federated reinforcement learning: techniques, applications, and open challenges. In IR.

[4] Hegiste, Vinit; Legler, Tatjana; Ruskowski, Martin (Eds.): Application of Federated Machine Learning in Manufacturing.

[5] V. Hegiste, T. Legler, K. Fridman and M. Ruskowski, "Federated Object Detection for Quality Inspection in Shared Production," 2023 Eighth International Conference on Fog and Mobile Edge Computing (FMEC), Tartu, Estonia, 2023, pp. 151-158.

[6] Legler, Tatjana, et al. "Addressing Heterogeneity in Federated Learning: Challenges and Solutions for a Shared Production Environment." CoRR (2024).

[7] Liang, Xinle, et al. "Federated transfer reinforcement learning for autonomous driving." Federated and Transfer Learning. Cham: Springer International Publishing, 2022. 357-371.

[8] Nair, Jayprakash S., et al. "On decentralizing federated reinforcement learning in multi-robot scenarios." 2022 7th South-East Europe Design Automation, Computer Engineering, Computer Networks and Social Media Conference (SEEDA-CECNSM). IEEE, 2022.

[9] Shivkumar, S., and AA Nippun Kumaar. "Manipulator Control using Federated Deep Reinforcement Learning." 2024 IEEE International Conference on Electronics, Computing and Communication Technologies (CONECCT). IEEE, 2024.

[10] Wang, Yue, Shida Zhong, and Tao Yuan. "Grasp Control Method for Robotic Manipulator Based on Federated Reinforcement Learning." 2024 7th International Conference on Advanced Algorithms and Control Engineering (ICAACE). IEEE, 2024.

[11] Yuan, Zhenyuan, Siyuan Xu, and Minghui Zhu. ”Federated reinforcement learning for robot motion planning with zero-shot generalization.” Automatica 166 (2024): 111709.

[12] Todorov, Emanuel, Tom Erez, and Yuval Tassa. ”Mujoco: A physics engine for model-based control.” 2012 IEEE/RSJ international conference on intelligent robots and systems. IEEE, 2012.

[13] Ortenzi, Valerio, et al. ”Hybrid motion/force control: a review.” Advanced Robotics 31.19-20 (2017): 1102-1113.

[14] Beltran-Hernandez, Cristian C., et al. ”Variable compliance control for robotic peg-in-hole assembly: A deep-reinforcement-learning approach.” Applied Sciences 10.19 (2020): 6923.