technische universität dortmund

Communication Networks

Master Thesis

Robust AI-based Control of 6G-Networked Humanoid Robots using Uncertainty-Aware World Models

Description

Humanoid and quadruped robots are regarded as a key technology for future rescue and industrial applications. To avoid energy-intensive computing hardware on the robot itself, Reinforcement Learning (RL)-based control policies are increasingly offloaded to Edge Computing and operated in a closed control loop, benefiting from low-latency 6G communications [1,4]. Bipedal robots impose extreme demands on the wireless link. The loop between perception, inference, and actuation usually tolerates only low-millisecond delays. Proactive Open RAN scheduling schemes such as O-RACES [1] reduce uplink latency and stabilize jitter. However, rare events are often unavoidable, and time-varying residual uplink delay remains in the control loop, which may destabilize conventional policies trained only on non-delayed sensor data without any robust world model.

The goal of this thesis is the development of a delay-robust control policy that enables stable movement under real, fluctuating network latency when offloaded to the edge cloud. At the core of the approach lies an uncertainty-aware world model [2, 3]. World models can be used to predict the current robot state from delayed observations, so that the policy acts on a compensated state estimate instead of the stale data. In high-uncertainty regions, e.g., during long latency outliers or out-of-distribution motions, the robot can fall back to a local conservative policy instead of following a hallucinated state. Complementarily, the policy is made robust by injected delays during training. The 6G network takes the complementary role of keeping the residual delay small and predictable in the average case, thereby operating the world model within its trustworthy, low-uncertainty regime.

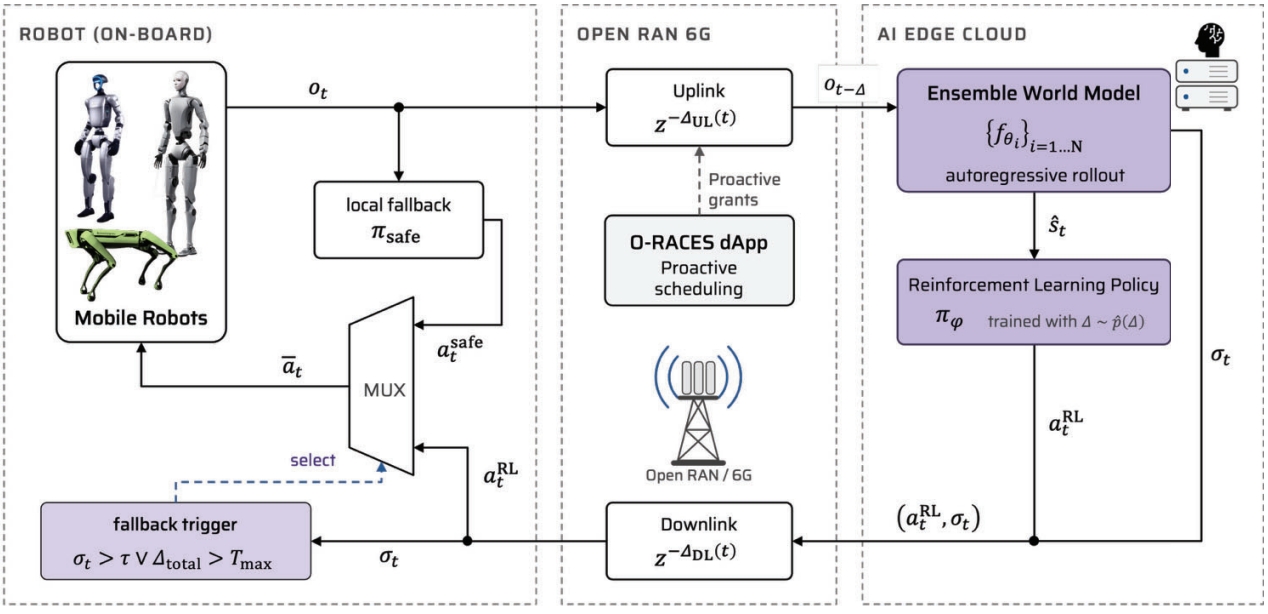

Figure 1: Edge-cloud control with world-model delay compensation and on-robot uncertainty-triggered fallback. The thesis focus is highlighted in violet.

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Proposed working points

- Familiarization with (Wireless) Networked Control Systems
- Creation of Reference Scenarios for Training in Isaac Sim
- Training in Isaac Lab/Sim incl. synthetically injected delay profiles
- Design and ablation of robustness mechanisms (delay-robust training, world-model compensation, uncertainty decision with local execution)
- Hybrid evaluation over in Isac Sim with emulated and real wireless link
- *Optional after successful completion in simulation: Deployment on real-world robots via AI edge cloud over the real radio network. Target platforms are humanoid and/or quadruped platforms.*

Requirements

- Strong interest in Reinforcement Learning, robotic control, and mobile radio communications
- Good Python and PyTorch skills; willingness to work into Isaac Lab / Isaac Sim and RSL-RL
- C++ knowledge is an advantage
- Good LaTeX and presentation skills, as well as excellent English language skills

References

[1] N. A. Wagner, C. Wietfeld, "O-RACES: Proactive AI-driven Scheduling in Open RAN for 6G-Networked Humanoid Robots," IEEE INFOCOM, Tokyo, Japan, May 2026.

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[4] N. A. Wagner, J. Eßer, I. F. Priyanta, F. Kurtz, M. Roidl, C. Wietfeld, "Real-Time Predictive Scheduling for Networked Robot Control Using Digital Twins and OpenRAN," IEEE Globecom Workshops (GC Wkshps), Cape Town, South Africa, Dec. 2024.

[5] T. Yu, G. Thomas, L. Yu, S. Ermon, J. Zou, S. Levine, C. Finn, T. Ma, "MOPO: Model-based Offline Policy Optimization," Advances in Neural Information Processing Systems (NeurIPS), 2020.

[6] S. Ramstedt, C. Pal, "Real-Time Reinforcement Learning," Advances in Neural Information Processing Systems (NeurIPS), 2019.

[7] B. Chen, M. Xu, L. Li, D. Zhao, "Delay-Aware Model-Based Reinforcement Learning for Continuous Control," Neurocomputing, vol. 450, pp. 119–128, 2021.

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