Collaborative Research: Physics-Model-Based Neural Networks Redesign for CPS Learning and Control

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Challenges:

- The current generation of DNNs cannot provide analyzable behaviors and verifiable properties necessary for safety assurance.
- Physics-model-based engineering methods provide analyzable behaviors and verifiable properties but do not match the performance of DNN systems.
- Trained DNN models in real CPS are not adaptive in real-time operating environments.

Solutions: Runtime Learning Machine

- (High assurance) HA-Teacher: Safety only! Physics-model-based real-time patch: real-time model, real-time control policy, and real-time control goal.
- (High performance) HP-Student: DRL-Agent. Self-Learn and Learn-from-HA-Teacher for a safe and high-performance action policy.
- Interaction: When HP-Student's action is unsafe, HP-Student backs up safety and Teaches HP-Student about safety.

Scientific Impact:

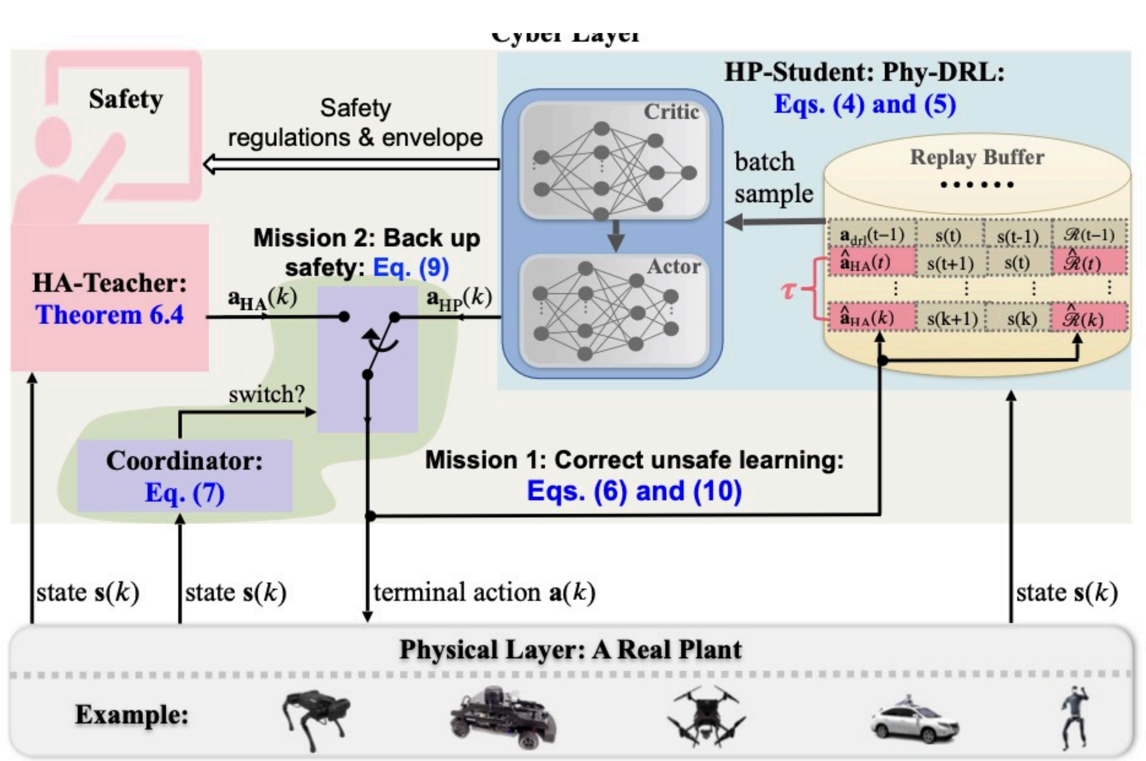
- Advance fundamentally integrating deep learning and robust control to enable nonstationary, safety- and time-critical CPS to operate safely with high performance.

Broad Impact: Academic and Technical Impact

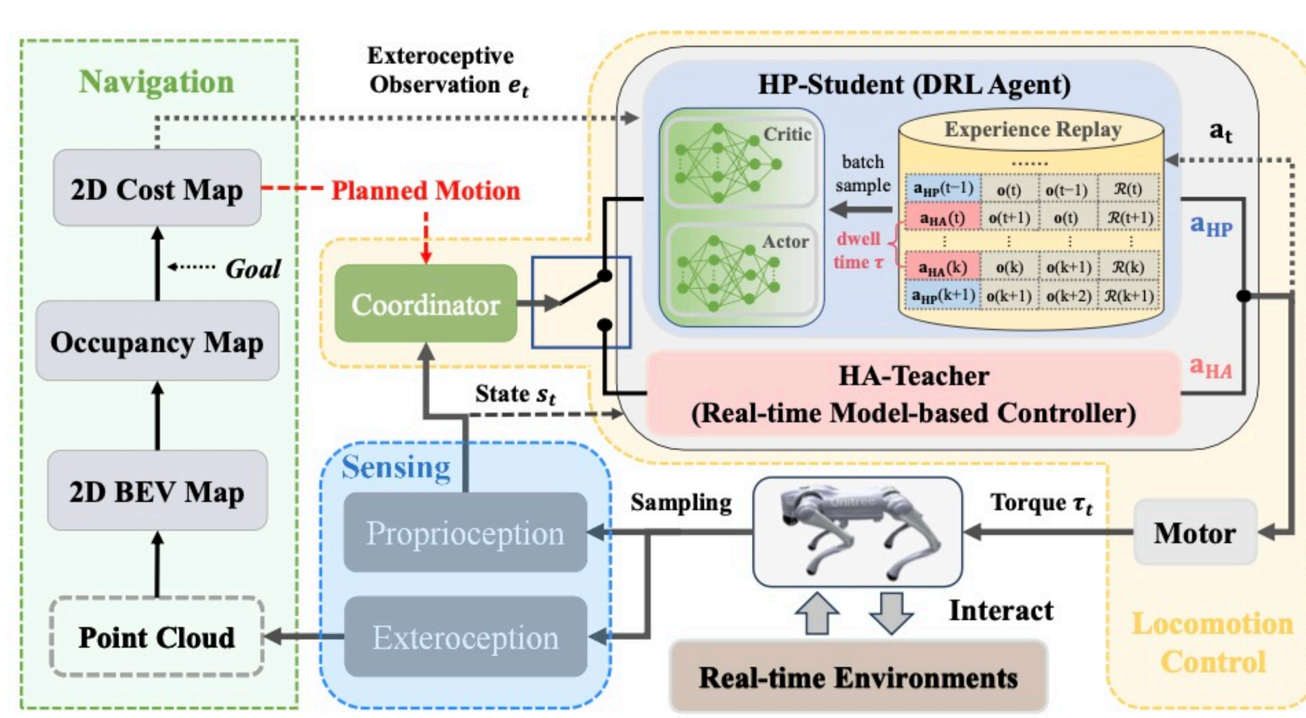
- Lead to a new paradigm in how DNNs can be redesigned trustworthily and applied safely to non-stationary, safety- and time-critical CPS.
- Will be readily transferred to industrial use cases to build new CPS infrastructure in modern society, greatly promoting industrial automation and boosting the economy.

Broad Impact: Potential Impact

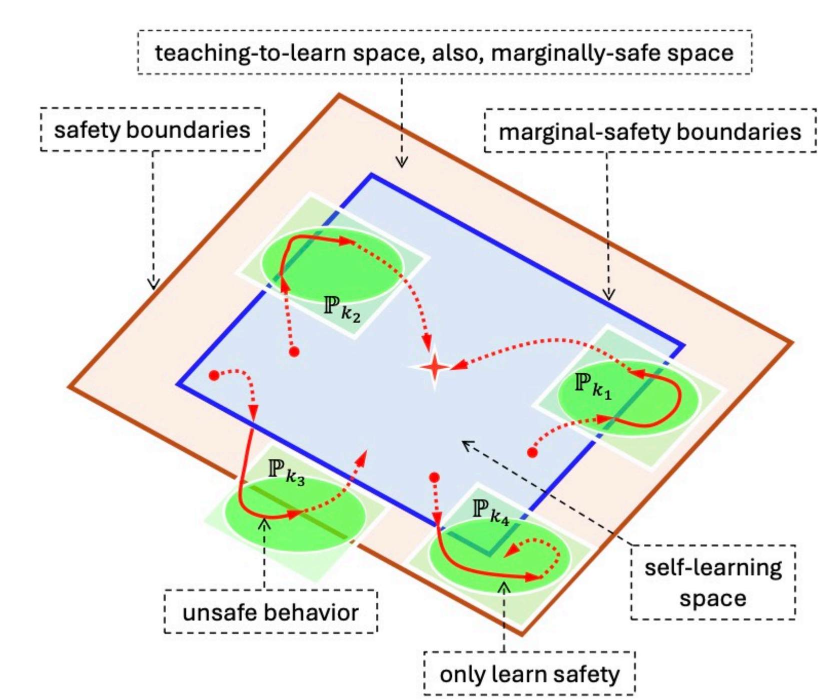
- The project will be a milestone toward the goals of DNN with explainable behavior and provable properties. The results will be broadly disseminated to the CPS, machine learning, and control communities through conference presentations, journal publications, and invited seminars.



The architecture of runtime learning machine



Application of quadruped robots



Green: real-time patches:
real-time physics-model-based controlled

Real testbeds

References

[1] Yihao Cai, Yanbing Mao,, Lui Sha, Hongpeng Cao, and Marco Caccamo, "Runtime Learning of Quadruped Robots in Wild Environments," submitted to the 2025 IEEE/RSJ International Conference on Intelligent Robots and Systems.

[2] Hongpeng Cao, Yanbing Mao, Yihao Cai, Lui Sha, and Marco Caccamo, "Runtime Learning machine," submitted to ACM Transactions on Cyber Physical Systems (Special Issue on Embodied Artificial Intelligence in Cyber-Physical Systems: Algorithms, Computing Systems, Applications, and Trustworthiness). https://openreview.net/pdf?id=KCTHM2Ffh3

[3] Hongpeng Cao, Yanbing Mao, Lui Sha, and Marco Caccamo, "Physics-Regulated Deep Reinforcement Learning: Invariant Embeddings," The International Conference on Learning Representations, Spotlight, pp. 1-45, 2024.

[4] Yanbing Mao, Lui Sha, Huajie Shao, Yuliang Gu, Qixin Wang, and Tarek Abdelzaher, "Phy-Taylor: Partially Physics-Knowledge-Enhanced Deep Neural Networks via NN Editing," IEEE Transactions on Neural Networks and Learning Systems, vol. 36, no. 1, pp. 447-461, 2025.

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