Evolutionary Computation and Reinforcement Learning for Cyber-physical System Design

Chengjie Lu[1,2]

Simula Research Laboratory[1], University of Oslo[2], Norway

Introduction

Context

Cyber-physical systems (CPSs):

1. Integrate computation, networking, and physical processes through constantly interacting with the physical environment.
2. A typical CPS consists of physical, communication, computation, and control components.
3. Computation component is the core of the whole system and embeds the decision-making strategy.

Challenges

CPS design is challenging:

1. CPS is designed to automatically perform different tasks under dynamic physical environments, which is complex and uncertain.
2. The increasing complexity and uncertainty of CPS often come up with unexpected and unpredictable behaviors of the systems.
3. Coordination among multiple agents in a CPS or different CPSs is important for decision-making in complex tasks.

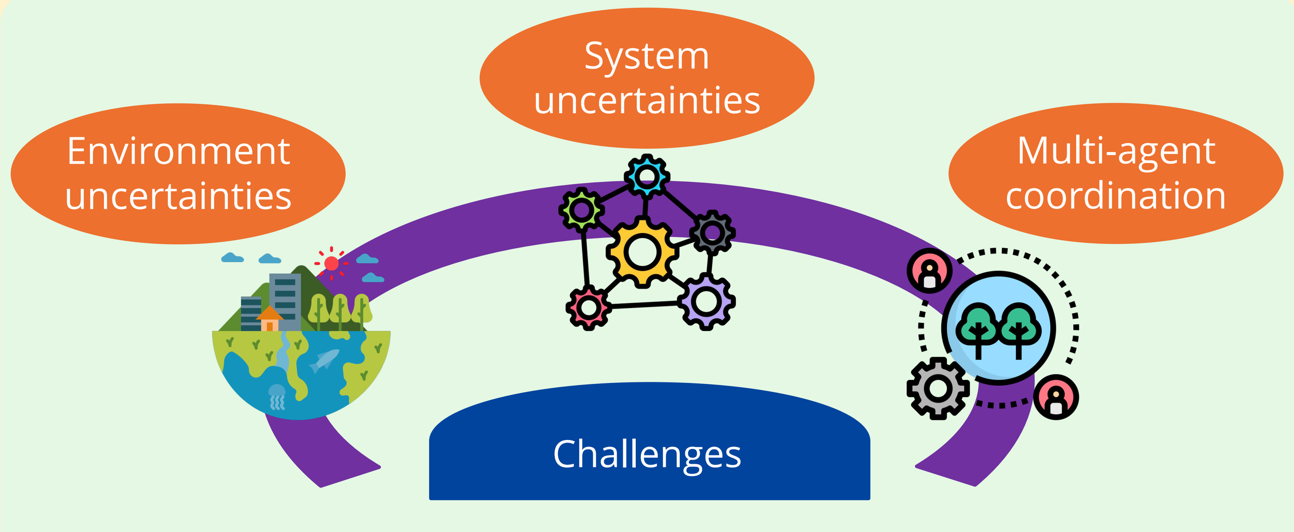


Figure 1. CPS design challenges

Objectives

Improve the ability of CPS in dealing with environment and system uncertainties	Design novel control policies to coordinate collaboration among agents	Design novel testing and evaluating approaches for testing CPS

Proposal

Research proposal:

1. We proposal to utilize evolutionary computation (EC) and reinforcement learning (RL) techniques to design novel control policies for CPS.
2. Novel CPS testing approaches will also be studied.

Evolutionary Computation & Reinforcement Learning

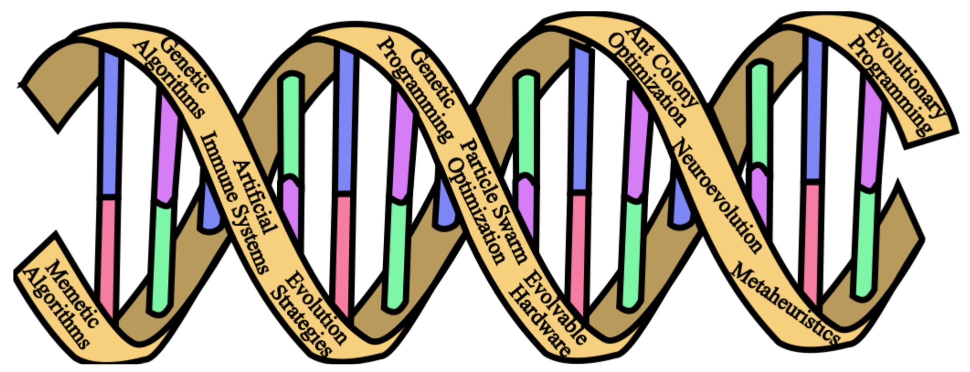


Figure 2. Evolutionary Computation

Special Issue "Evolutionary Computation: Theories, Techniques, and Applications"

Evolutionary computation (EC)

1. EC is inspired by models of natural genetics and evolutionary processes.
2. EC is used widely in complex optimization problems and for continuous optimization.
3. Evolutionary algorithms include genetic algorithms, evolutionary programming, and etc.

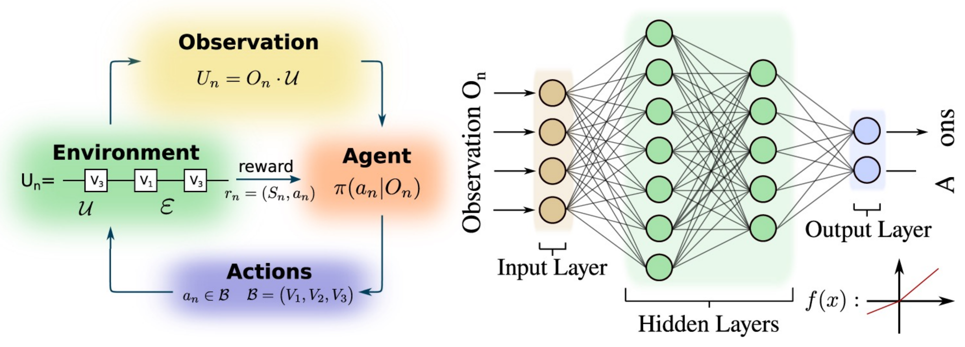


Figure 3. Reinforcement learning

Moro, Lorenzo, et al. "Quantum compiling by deep reinforcement learning." Communications Physics 4.1 (2021): 178.

Reinforcement learning (RL)

1. RL is concerned with learning optimal policies through agents interacting with unknown environments.
2. RL has been widely used in problems that require dynamic adaption.
3. Deep RL combines RL and deep learning, allowing agents to make decisions under high dimensional environments.

Research Questions & Expected Outputs

	RQ1:	RQ2:	RQ3:
Research Questions	How to utilize EC and RL to improve CPS's ability in dealing with the uncertainty and complexity of the environment?	How to employ EC and RL to coordinate collaboration among multiple vehicles for complex tasks?	How to effectively and efficiently evaluate the ability of CPSs to deal with dynamic and uncertain environments?
Expected Outputs	1. CPS design approach that can take advantage of EC and RL. 2. Novel hybrid algorithms that combine EC and RL.	1. Novel multi-agent control policies that can coordinate multiple agents for complex tasks.	1. Novel testing strategies that can adapt to dynamic environments and generate test cases for CPSs. 2. Novel Test optimization approach.

Empirical Design & Evaluation

Autonomous driving system (ADS)

1. We plane to focus on the domain of autonomous driving.
2. ADSs are typical CPSs that place high requirements on safety and reliable at the design stage.
3. ADS is usually composed of multiple components to coordinate different tasks.

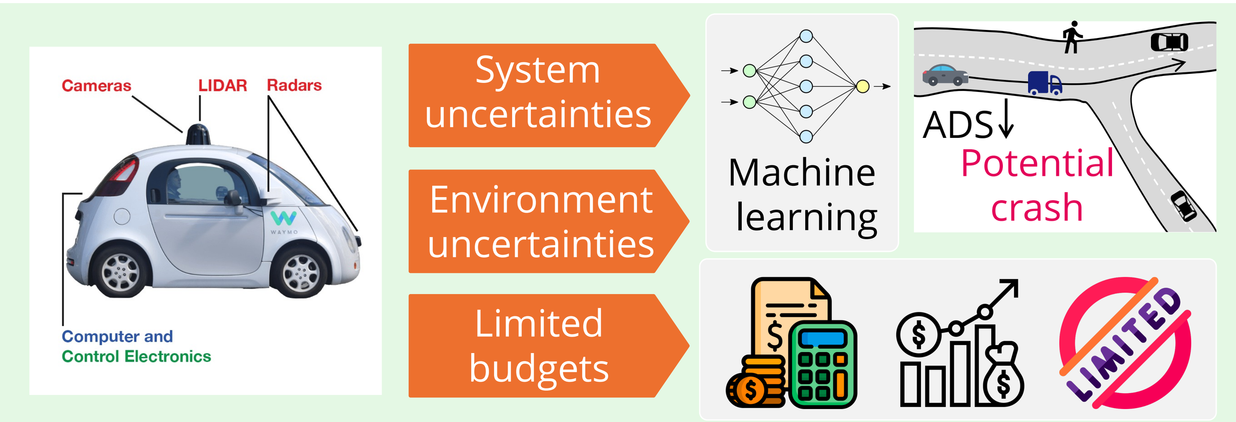


Figure 4. ADS design challenges

Experiment design

1. We will select different tasks to evaluate the design control policies.
2. The ADS testing approaches will be evaluated on various ADS.

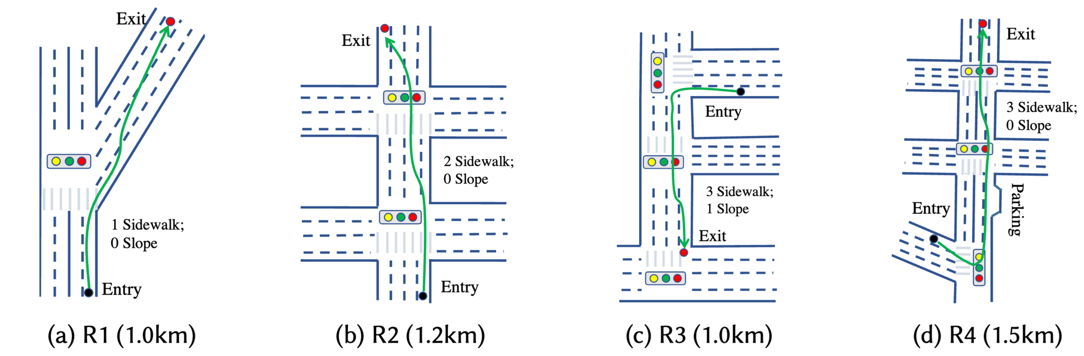


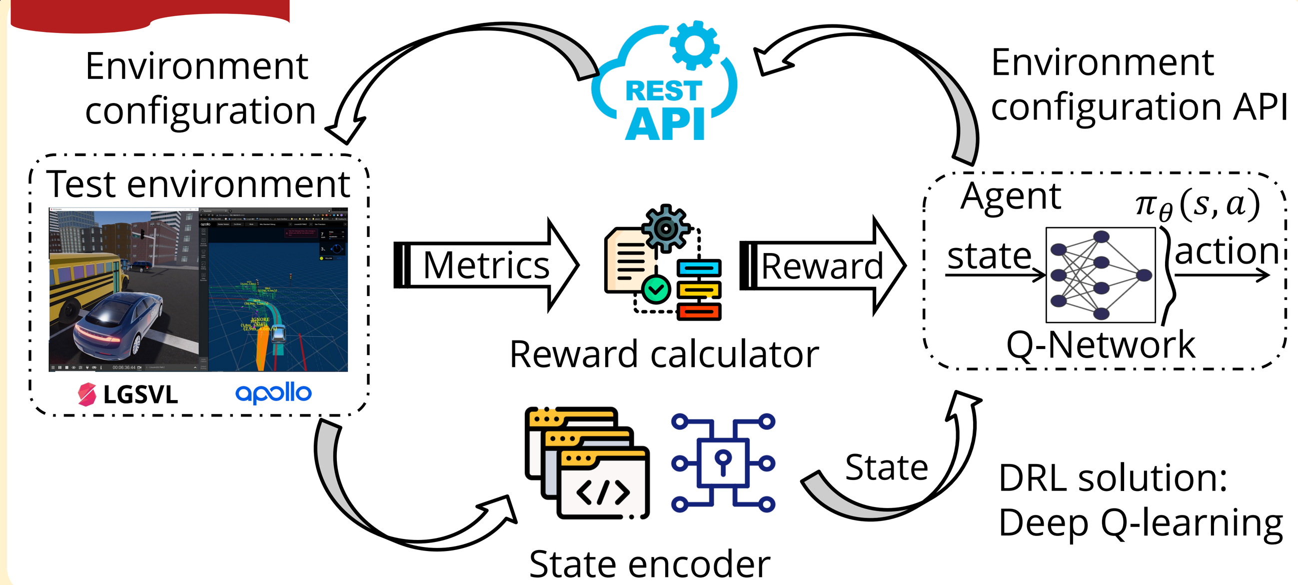
Figure 5. Examples of driving tasks [1]

Evaluation metrics

Safety	Comfort	Algorithm
Collision, Time to Collision, Collision Probability, …	Changing rate of acceleration, Stability , …	Accuracy, Precision, Recall, F1-score, …

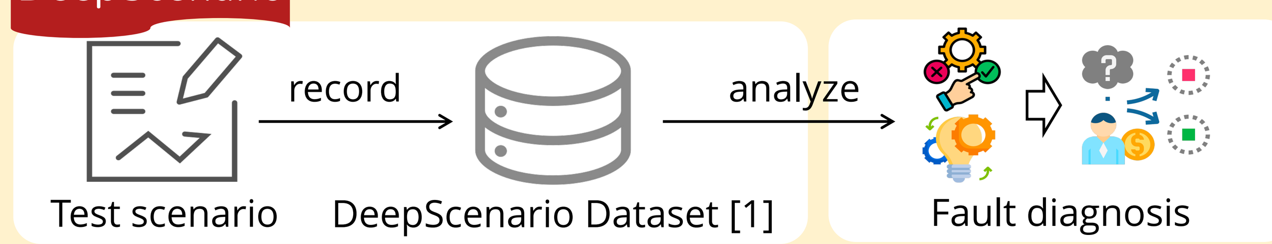
Current Research Stage

RLTester



RLTester is accepted by **ICSE 2023** Student Research Competition.

DeepScenario



The dataset is accepted by **MSR 2023** Data and Tool Showcase Track.

References

[1] *DeepScenario repository: An Open Driving Scenario Dataset for Autonomous Driving System Testing. MSR 2023.* https://github.com/Simula-COMPLEX/DeepScenario

simula UiO University of Oslo

Email: chengjielu@simula.no