CoTV: Cooperative Control for Traffic Light Signals and Connected Autonomous Vehicles using Deep Reinforcement Learning

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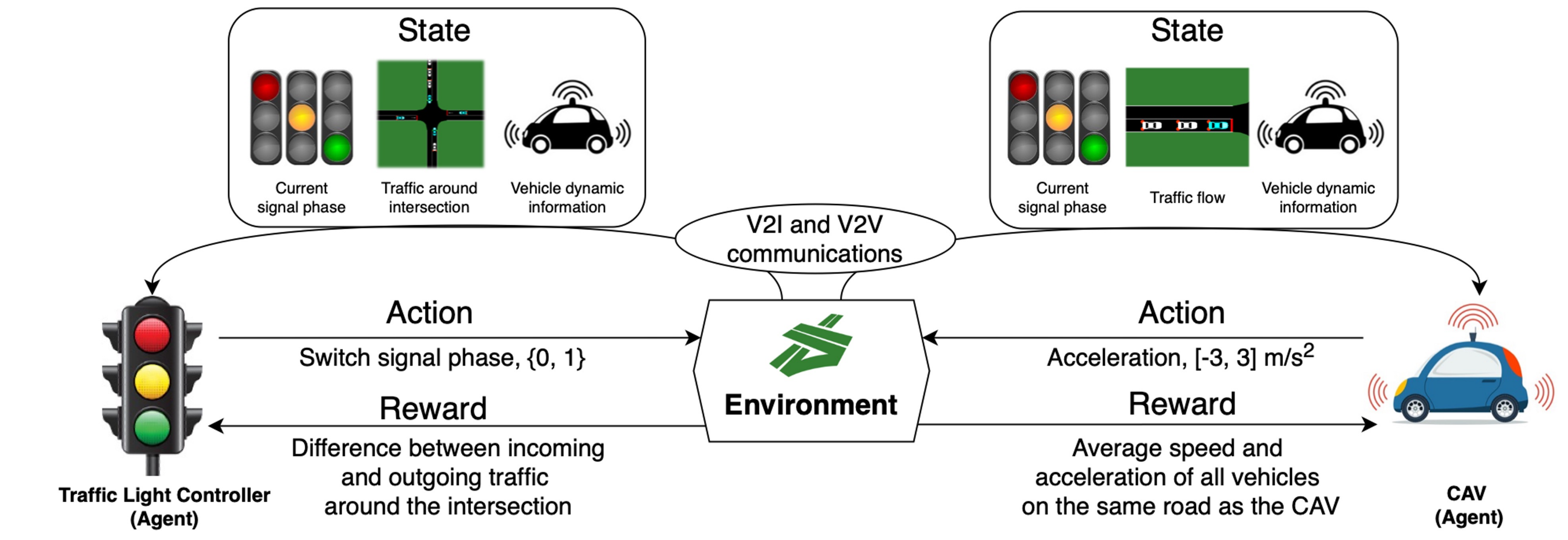
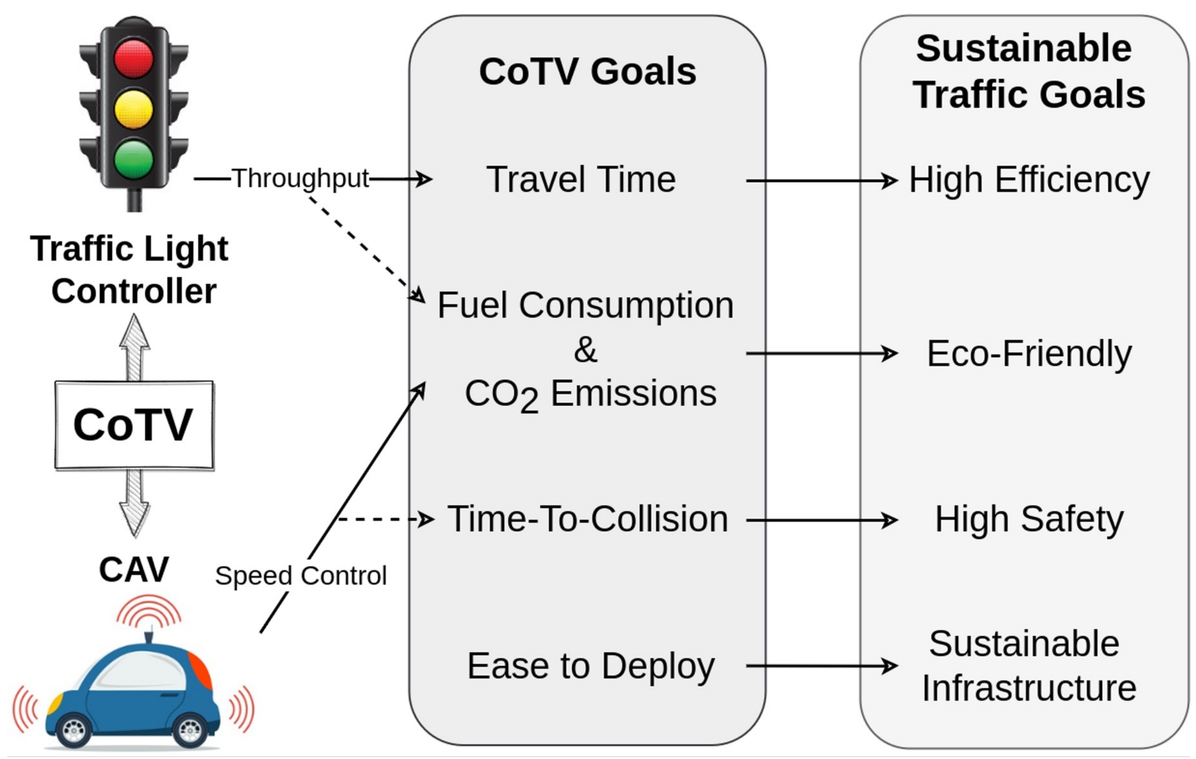


Motivation

Our CoTV[1] coordinates the two different types of agents, traffic light controllers and CAVs, to achieve a more comprehensive set of sustainable traffic goals.



Methodology

- The DRL algorithm in CoTV is Proximal Policy Optimisation (PPO).
- Improved agent designs for CAVs and traffic light controllers, including state, action and reward, enable complementary traffic improvements.
- The cooperation schemes among agents rely on state information exchanged via Vehicle-To-Everything (V2X) communications.
- CoTV selects the closest CAV to the intersection on each incoming road as the CAV agent, which addresses scalability issues.
- The low-cost agent communication of CoTV requires only transmission rates below 100 Kbps.

CoTV compared with, except [2, 3]:

- Baseline: static traffic lights and human-driven vehicles
- GLOSA: traditional joint control method
- I-CoTV: independent training without state exchange
- M-CoTV: agent cooperation in action and state
- CoTV*: all possible CAVs as agents of CoTV

Highlights

- Effective cooperation schemes between CAVs and traffic light controllers.
- Scalable to complex urban scenarios by avoiding cooperation with excessive CAV agents.
- Efficient communication exchange schemes between CAV and traffic light controllers.

Results

The experiments are conducted under grid maps and a more realistic urban road network.

Method	Travel time (s)	Fuel (l/100km)	TTC
Baseline	59.33	10.98	1212.67
FlowCAV[2]	+0.10%	+1.64%	+0.87%
PressLight[3]	-24.29%	-22.68%	-61.81%
GLOSA	-23.48%	-22.95%	-55.02%
CoTV	**-29.61%**	**-27.41%**	**-83.84%**

Table 1. Performance comparison of traffic control methods under Dublin scenario.

Method	Travel time (s)	Fuel (l/100km)	TTC	Training time (h)
I-CoTV	49.21	9.19	489.78	1.36
M-CoTV	47.53	10.44	660.08	2.00
CoTV*	43.42	7.98	219.67	2.37
CoTV	**41.76**	**7.97**	**195.94**	**1.33**

Table 2. Performance comparison of CoTV with other variants under Dublin scenario.

We also demonstrate the robustness of CoTV when deployed in realistic mixed-autonomy traffic.

Fig.1 shows that the travel time of CoTV tends to decrease as the CAV penetration rate increases.

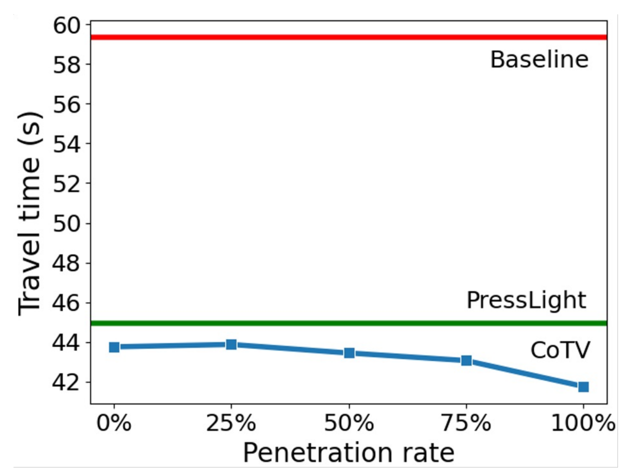


Fig 1. Average travel time of CoTV in mixed-autonomy traffic under Dublin scenario.

Conclusion & Future Work

The proposed CoTV can significantly improve traffic efficiency and safety, ease the deployment, and facilitate training convergence. In the future, we will further enhance the practicability of CoTV in complex urban traffic scenarios.

References

1. Guo, Jiaying, Long Cheng, and Shen Wang. "CoTV: Cooperative Control for Traffic Light Signals and Connected Autonomous Vehicles Using Deep Reinforcement Learning." IEEE Transactions on Intelligent Transportation Systems (2023).
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3. Wei, Hua, et al. "PressLight: Learning max pressure control to coordinate traffic signals in arterial network." Proceedings of the 25th ACM SIGKDD International Conference on Knowledge Discovery & Data Mining. 2019.

https://github.com/Guojyjy/CoTV
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