01

Learning of collective intelligence via digital twins

Distributed traffic coordination without traffic signals

Abstract

In the era of autonomous vehicles, traffic coordination systems using signals will be replaced. In IOWN's signal-free mobility, it is suggested that vehicles will autonomously transition their states (e.g., speed acceleration, handle steering, and position) via communication among vehicles. For signal-free mobility, a recurrent neural network (RNN) architecture is proposed which alternately iterates (i) communication between closely positioned vehicles (token exchange to prevent vehicle collisions) and (ii) local state updates. Since our method can be performed in a distributed manner, it is suitable to control a large number of vehicles in a city in real-time. Via training through digital twins (simulation system linked with the real world), we will obtain a collective intelligence model. We confirmed the overall efficiency of trained RNN through traffic coordination tests in digital twins and real experiments using real small vehicles.

Goal

The concept of signal-free mobility, in which a set of automated vehicles coordinates their traffic without using traffic signals, is shown in [1]. To realize this concept, we have studied on a distributed control problem to reduce travel/transportation time to the limit while vehicles are collision-free [2].

Constrained dynamics learning

Traffic coordination in which each vehicle updates its states (e.g., speed, position) while imposing constraints on them to prevent collisions can be represented by an ordinary differential equation (ODE).

$$\frac{d\boldsymbol{x}}{dt} = \overbrace{M_1(\boldsymbol{x}, t, \theta, \boldsymbol{A}, \boldsymbol{b})}^{\text{State update in local vehicle}} + \overbrace{M_2(\boldsymbol{x}, t, \boldsymbol{A}, \boldsymbol{b})}^{\text{Communication between vehicles}}$$

By discretizing this ODE, we constructed a recurrent neural network (RNN) in which V vehicles evolve their states K times. As shown in the figure below, this RNN consists of alternatingly repeat of (i) local state updates ($\boldsymbol{x}$), (ii) communication between vehicles to exchange token for satisfying collision-free constraints, and (iii) local updates of input/constraint parameters ($\boldsymbol{A}$, $\boldsymbol{b}$). The size of this RNN is huge with a width of V and a depth of K. However, it is composed of a set of operations that can be parallelized, allowing for real-time state updates as a forward propagation. Meanwhile for backward propagation, driving dynamics model ($\boldsymbol{\theta}$) is optimized to have a small loss score designed to increase the averaged vehicle speed.

Image of process at time t

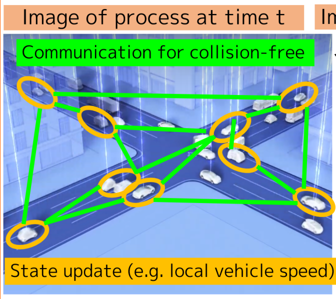
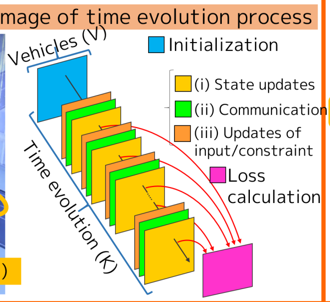


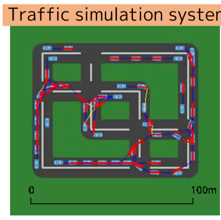
Image of time evolution process



Dynamics model training using digital twins

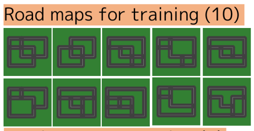
To efficiently train driving dynamics model, we constructed a traffic simulation system that evolves states in digital twins of V vehicles and roads linked to them in real world. By driving digital twins of vehicles on various road maps including virtual ones (see figure below), we can efficiently collect data sets. We optimized driving dynamics mode; though R=300 round iterations of simulation (forward propagations) and backward propagations.

Traffic simulation system

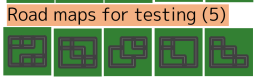


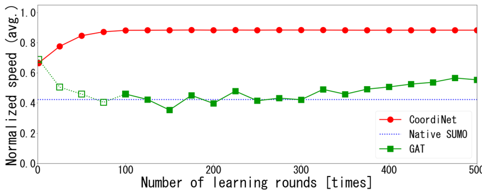
The proposed method showed an averaged vehicle speed improvement of about 30% compared to the initialization (random) (red line). The higher averaged speed compared to the unconstrained graph neural network (green line, GAT[3],) and the untrainable traffic simulator (blue dot line, SUMO[4]) confirm the effectiveness of the proposed method.

Road maps for training (10)



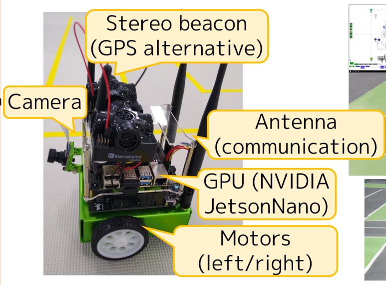
Road maps for testing (5)

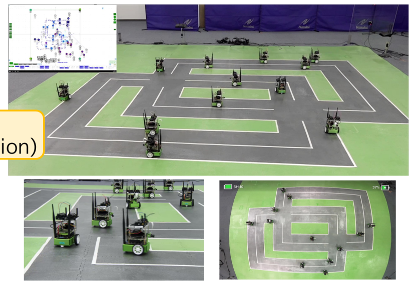




Feedback to real world system

We constructed a real world system of signal-free mobility using a set of small real vehicles (see figure below) and conducted experiments to feedback the optimized driving dynamics model to the real world. We confirmed that each vehicle autonomously run without collisions by exchanging tokens to each other.





References

[1] IONW conceptual video, “Mobility by IOWN,” YouTube, 2019

[2] K. Niwa, N. Ueda, H. Sawada, A. Fujino, S. Takeda, B. Kleijn, G. Zhang, “CoordiNet: Constrained dynamics learning for state coordination over graph,” in *Proc. the 26th ACM SIGKDD International Conference on Knowledge Discovery & Data Mining (KDD 2022)*, 2022 (under review).

[3] P. Veličković, G. Cucurull, A. Casanova, A. Romero, P. Lio, and Y. Bengio, “Graph attention networks,” *arXiv preprint arXiv:1710.10903*, 2017.

[4] Simulation of Urban MObility (SUMO), https://www.eclipse.org/sumo/

Contact

Kenta Niwa / Learning and Intelligent Systems Research Group, Innovative Communication Laboratory

Email: cs-openhouse-ml@hco.ntt.co.jp