# On-board Traffic Prediction Via V2X Connectivity

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## 1. Introduction

Vehicles and the traffic infrastructure become increasingly connected by the help of emerging vehicle-to-everything (V2X) communication technologies. This facilitates the development of connected automated vehicles (CAVs), which are expected to significantly impact road transportation [1, 2, 3, 4, 5, 6, 7, 8].

CAVs rely on sensory information as well as on communicated messages that contain information about the motion of other vehicles, such as position and speed data, which implicitly characterizes even the traffic flow itself [9, 10, 11]. Although the penetration of connectivity is expected to increase in the near term, there will exist a considerable time period with mixed traffic consisting of both connected and non-connected vehicles. If the penetration of connectivity is low, the information received by the CAV may be transmitted from a vehicle that is farther away; see the illustration in Fig. 1(a). In this work we consider how to utilize such information.

In particular, we investigate how the CAV can make on-board prediction about the downstream traffic based on trajectory information communicated from a vehicle far ahead. Such connectivity-based traffic prediction allows the CAV to estimate the motion of preceding non-connected vehicles, as well as its own anticipated future behavior in traffic. As opposed to commonly available traffic provider data, connectivity-based on-board predictions can be made real time and can be tailored to the needs of the CAV. Thus, they can potentially be used in the control design of the CAV to optimize its operation. This also facilitates smooth driving, which is beneficial for both the CAV and the surrounding traffic.

## 2. Methodology

We use traffic models to make predictions about the future motion of a selected ego vehicle based on the trajectory data communicated from a lead vehicle upstream; see Fig. 1(a). In order to directly take into account the trajectory data, the model must be formulated in the vehicle-based (Lagrangian) framework via the position $X(n,t)$ of the vehicles in traffic. For example, one may consider car-following models

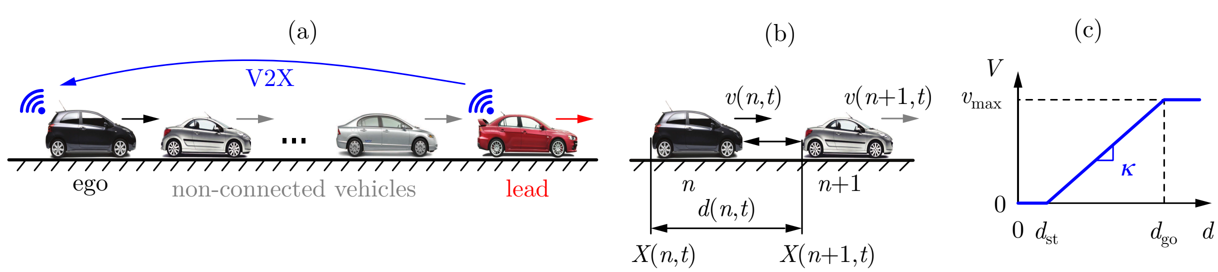


Figure 1. Illustration of (a) the scenario assumed for connectivity-based traffic prediction, (b) the car-following model, and (c) its range policy.

such as [12]

$$\partial_t X(n,t) = V\big(X(n+1,t-\tau) - X(n,t-\tau)\big)\,, \tag{1}$$

which states that vehicle $n$ controls its speed according to the distance $d(n,t) = X(n+1,t) - X(n,t)$ from its predecessor $n+1$; see Fig. 1(b). A key ingredient of this model is the time delay $\tau$ that accounts for driver reaction time or actuation, communication and feedback delays. The speed-distance relationship (range policy) can be given for example by the function shown in Fig. 1(c).

Alternatively, continuum traffic flow models can also be used. The most well-known one is the Lighthill-Whitham-Richards (LWR) model [13, 14], which can be written in the vehicle-fixed frame as [15]

$$\partial_t X(n,t) = V\big(\partial_n X(n,t)\big)\,. \tag{2}$$

Note that (2) does not involve the effect of time delay, although it significantly affects traffic dynamics [16]. The introduction of delays into continuum models is nontrivial [17, 18, 19, 20]. One possible approach is to build an approximate continuum counterpart of (1), which is given by [21, 22]

$$\sum_{m=0}^{M_v} \frac{(-1)^m}{m!} \partial_n^m \partial_t X(n,t) = V\left( - \sum_{m=1}^{M_X} \frac{(-1)^m}{m!} \partial_n^m X(n,t-\tau) \right), \tag{3}$$

where $M_X$ and $M_v$ indicate the order of the model. Note that $M_X = 1$, $M_v = 0$ reduces to (2) when $\tau = 0$, and the higher order terms ($M_X \geq 1$, $M_v \geq 1$) are required to introduce the delay $\tau > 0$.

When a CAV receives trajectory data from another connected vehicle downstream, it can use the data as boundary condition to simulate model (3) forward in time. The simulated trajectories represent a prediction of the traffic flow, including the anticipated future motion of the CAV and its predecessors.

## 3. Results

Figure 2 illustrates the process of connectivity-based traffic prediction. Here, we used experimental data of two connected vehicles that was recorded in a traffic jam on public roads in the scenario of Fig. 2(a). The details of the prediction is explained in Fig. 2(b). We consider that measured trajectory data from a downstream lead vehicle (red solid) is transmitted via V2X connectivity to an ego vehicle (black solid), who makes a prediction (blue solid) about its future motion (black dashed). To make a prediction, the lead vehicle's trajectory is utilized as boundary condition and model (3) is simulated to estimate

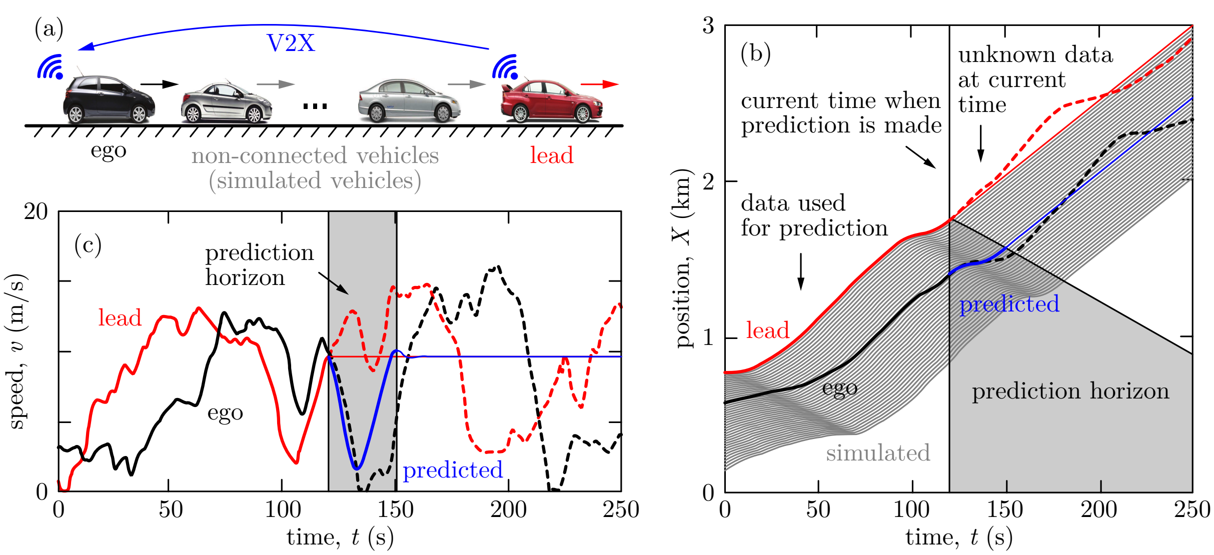


Figure 2. Connectivity-based on-board traffic prediction via model (3) for the scenario shown in panel (a). Red: trajectory of the lead vehicle that is communicated by V2X, black: trajectory of the ego vehicle, gray: simulated trajectories, blue: predicted trajectory of the ego vehicle; including (b) the positions and (c) the speeds. The relevant prediction horizon is shaded with gray.

trajectories between the lead and ego vehicles (gray lines). Then, the closest simulated trajectory to the ego vehicle's trajectory is selected as a prediction about the ego vehicle's future motion. Figure 2(c) shows the corresponding speed prediction. The model parameters used in Fig. 2 are $M_X = M_v = 2$, $d_{\mathrm{st}} = 10\,\mathrm{m}$, $v_{\max} = 30\,\mathrm{m/s}$, $1/\kappa = 1.5\,\mathrm{s}$ and $\tau = 1\,\mathrm{s}$.

Note that trajectory prediction is possible over a certain prediction horizon; see the gray shading in Fig. 2(b). The horizon decreases with the speeds of the traffic flow and the congestion waves. Furthermore, the farther the ego vehicle is from the lead vehicle at the time of prediction, the larger the prediction horizon. Thus, in order to reach a large enough horizon, V2X connectivity must provide information from large enough distance downstream the ego vehicle. This prescribes technological requirements regarding the range of V2X connectivity. Beyond the horizon, the lead vehicle's future trajectory (red dashed) must also be assumed (thin red) in order to further predict the ego vehicle's trajectory (thin blue), but this assumption does not influence the prediction within the prediction horizon.

## 4. Conclusion

The method described above allows V2X connectivity-based traffic prediction for CAVs. Since the predictions can be tailored to the needs of the CAV and can be made on board, the CAV may exploit them to plan and control its motion or to optimize its operation. The prediction horizon depends on the state of traffic (distance and speed of vehicles, speed of congestion waves), while the prediction accuracy is determined by the utilized traffic model. As a future work, we intend to accommodate this method to more sophisticated traffic models, which are formulated at the acceleration level. These models directly take into account the acceleration limits of vehicles and are more suitable for the control design of CAVs. We also plan to investigate how predictions are affected when the model parameters (such as the delay $\tau$) are varying in time $t$ or over the vehicle index $n$. These account for the uncertainties in (human) driving behavior over time and for the heterogeneity of traffic involving different kinds of vehicles and drivers.

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## References

[1] S. Cui, B. Seibold, R. Stern, D. B. Work, Stabilizing traffic flow via a single autonomous vehicle: Possibilities and limitations, in: Proceedings of the 2017 IEEE Intelligent Vehicles Symposium, Los Angeles, CA, USA, 2017, pp. 1336–1341.

[2] C. Wu, A. Kreidieh, K. Parvate, E. Vinitsky, A. M. Bayen, Flow: Architecture and benchmarking for reinforcement learning in traffic control, arXiv preprint (arXiv:1710.05465).

[3] M. Čičić, K. H. Johansson, Traffic regulation via individually controlled automated vehicles: a cell transmission model approach, in: Proceedings of the 21st International Conference on Intelligent Transportation Systems, Maui, HI, USA, 2018, pp. 766–771.

[4] A. R. Kreidieh, C. Wu, A. M. Bayen, Dissipating stop-and-go waves in closed and open networks via deep reinforcement learning, in: Proceedings of the 21st International Conference on Intelligent Transportation Systems, Maui, HI, USA, 2018, pp. 1475–1480.

[5] A. Spiliopoulou, D. Manolis, F. Vandorou, M. Papageorgiou, Adaptive cruise control operation for improved motorway traffic flow, Transportation Research Record 2672 (22) (2018) 24–35.

[6] R. E. Stern, S. Cui, M. L. Delle Monache, R. Bhadani, M. Bunting, M. Churchill, N. Hamilton, R. Haulcy, H. Pohlmann, F. Wu, B. Piccoli, B. Seibold, J. Sprinkle, D. B. Work, Dissipation of stop-and-go waves via control of autonomous vehicles: Field experiments, Transportation Research Part C 89 (2018) 205–221.

[7] C. Wu, A. M. Bayen, A. Mehta, Stabilizing traffic with autonomous vehicles, in: Proceedings of the 2018 IEEE International Conference on Robotics and Automation, Brisbane, Australia, 2018, pp. 1–7.

[8] Y. Zheng, J. Wang, K. Li, Smoothing traffic flow via control of autonomous vehicles, arXiv preprint (arXiv:1812.09544).

[9] J. C. Herrera, D. B. Work, R. Herring, X. Ban, Q. Jacobson, A. M. Bayen, Evaluation of traffic data obtained via GPS-enabled mobile phones: The Mobile Century field experiment, Transportation Research Part C 18 (4) (2010) 568–583.

[10] D. B. Work, A. M. Bayen, Impacts of the mobile internet on transportation cyberphysical systems: Traffic monitoring using smartphones, in: Proceedings of the National Workshop for Research on High-Confidence Transportation Cyber-Physical Systems: Automotive, Aviation and Rail, Washington, DC, USA, 2008.

[11] D. B. Work, O.-P. Tossavainen, Q. Jacobson, A. M. Bayen, Lagrangian sensing: Traffic estimation with mobile devices, in: Proceedings of the American Control Conference, St. Louis, MO, USA, 2009, pp. 1536–1543.

[12] Y. Igarashi, K. Itoh, K. Nakanishi, K. Ogura, K. Yokokawa, Bifurcation phenomena in the optimal velocity model for traffic flow, Physical Review E 64 (4) (2001) 047102 (4 pages).

[13] M. J. Lighthill, G. B. Whitham, On kinematic waves II. A theory of traffic flow on long crowded roads, Proceedings of the Royal Society A - Mathematical, Physical and Engineering Sciences 229 (1178) (1955) 317–345.

[14] P. I. Richards, Shock waves on the highway, Operations Research 4 (1) (1956) 42–51.

[15] L. Leclercq, J. Laval, E. Chevallier, The Lagrangian coordinates and what it means for first order traffic flow models, in: Proceedings of the 17th International Symposium on Transportation and Traffic Theory, 2007, pp. 735–753.

[16] G. Orosz, R. E. Wilson, G. Stépán, Traffic jams: dynamics and control, Philosophical Transactions of the Royal Society A: Mathematical, Physical and Engineering Sciences 368 (1928) (2010) 4455–4479.

[17] D. Ngoduy, Generalized macroscopic traffic model with time delay, Nonlinear Dynamics 77 (1–2) (2014) 289–296.

[18] M. Burger, S. Göttlich, T. Jung, Derivation of a first order traffic flow model of Lighthill-Whitham-Richards type, in: Proceedings of the 15th IFAC Symposium on Control in Transportation Systems, Vol. 51, 2018, pp. 49–54.

[19] A. Tordeux, G. Costeseque, M. Herty, A. Seyfried, From traffic and pedestrian follow-the-leader models with reaction time to first order convection-diffusion flow models, SIAM Journal on Applied Mathematics 78 (1) (2018) 63–79.

[20] M. Burger, S. Göttlich, T. Jung, Derivation of second order traffic flow models with time delays, Networks & Heterogeneous Media 14 (2) (2019) 265–288.

[21] T. G. Molnár, D. Upadhyay, M. Hopka, M. Van Nieuwstadt, G. Orosz, Lagrangian models for controlling large-scale heterogeneous traffic, in: Proceedings of the 58th IEEE Conference on Decision and Control, Nice, France, 2019, accepted.

[22] T. G. Molnár, D. Upadhyay, M. Hopka, M. Van Nieuwstadt, G. Orosz, Exploiting V2X connectivity by delayed Lagrangian continuum traffic models, Transportation Research Part C: Emerging Technologies, to be submitted.