Lookup Table-Based Consensus Algorithm for Real-Time Longitudinal Motion Control of Connected and Automated Vehicles

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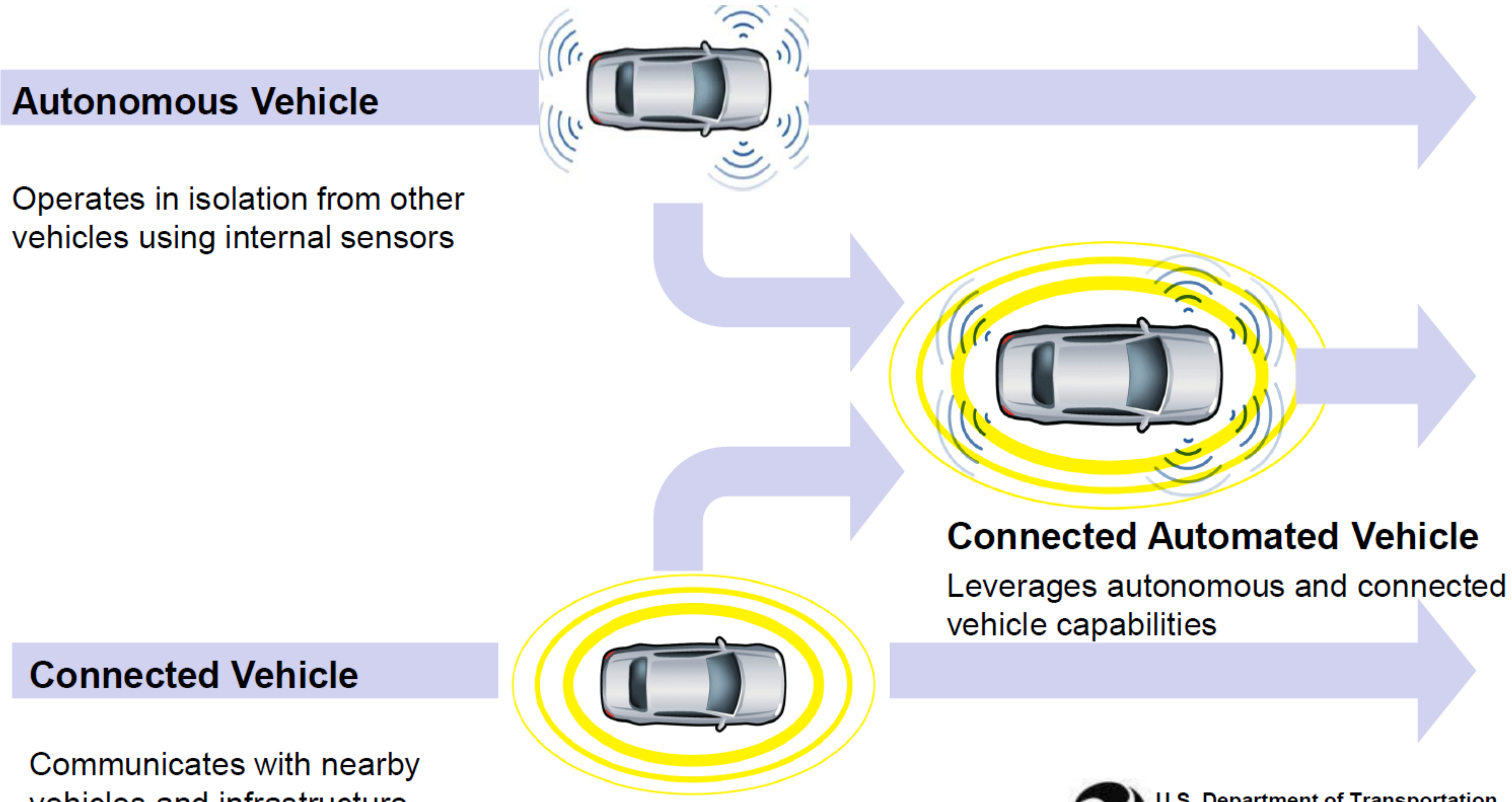
INTRODUCTION AND BACKGROUND

Connected and Automated Vehicles



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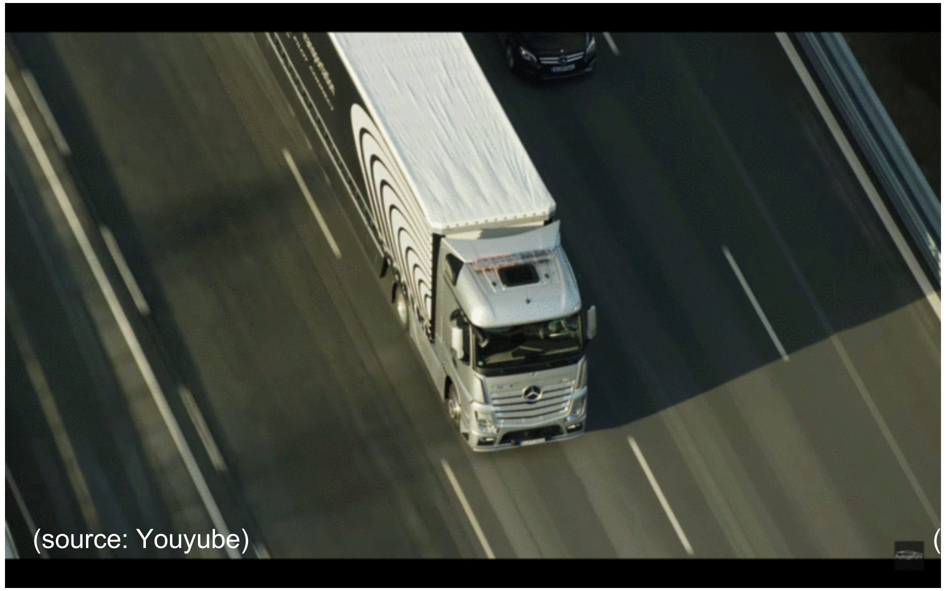
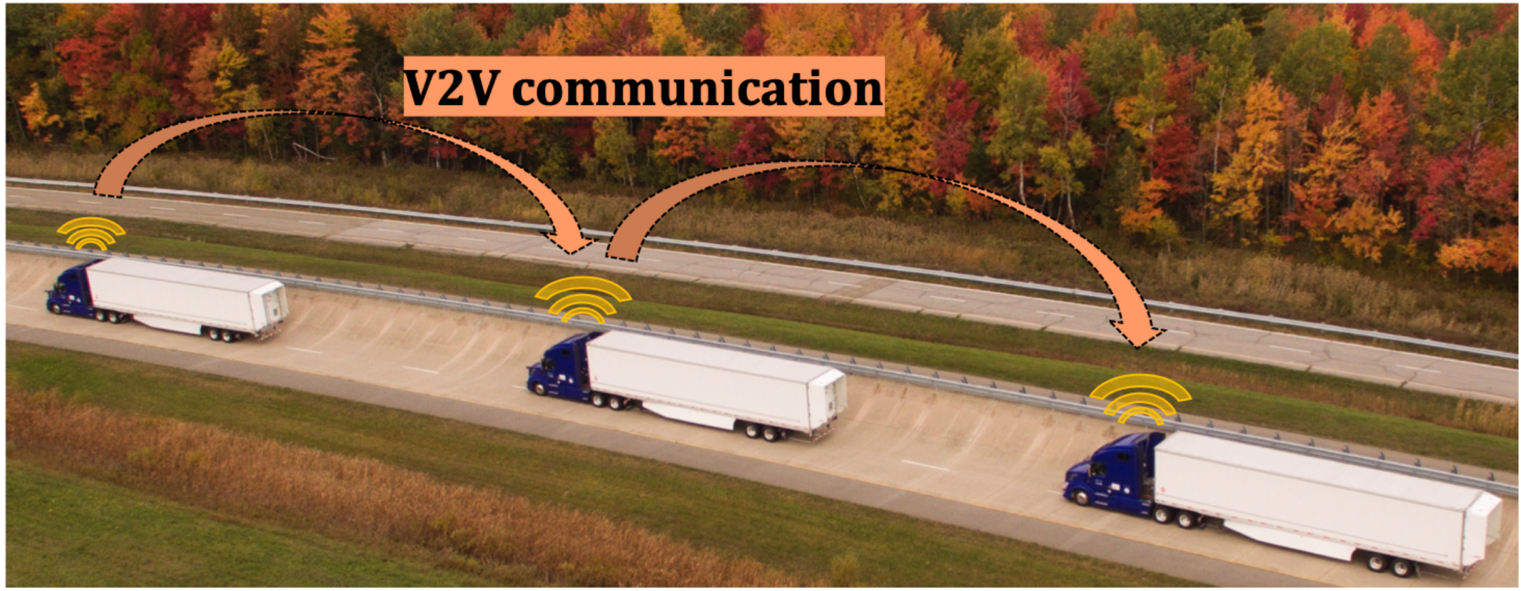
Cooperative Adaptive Cruise Control

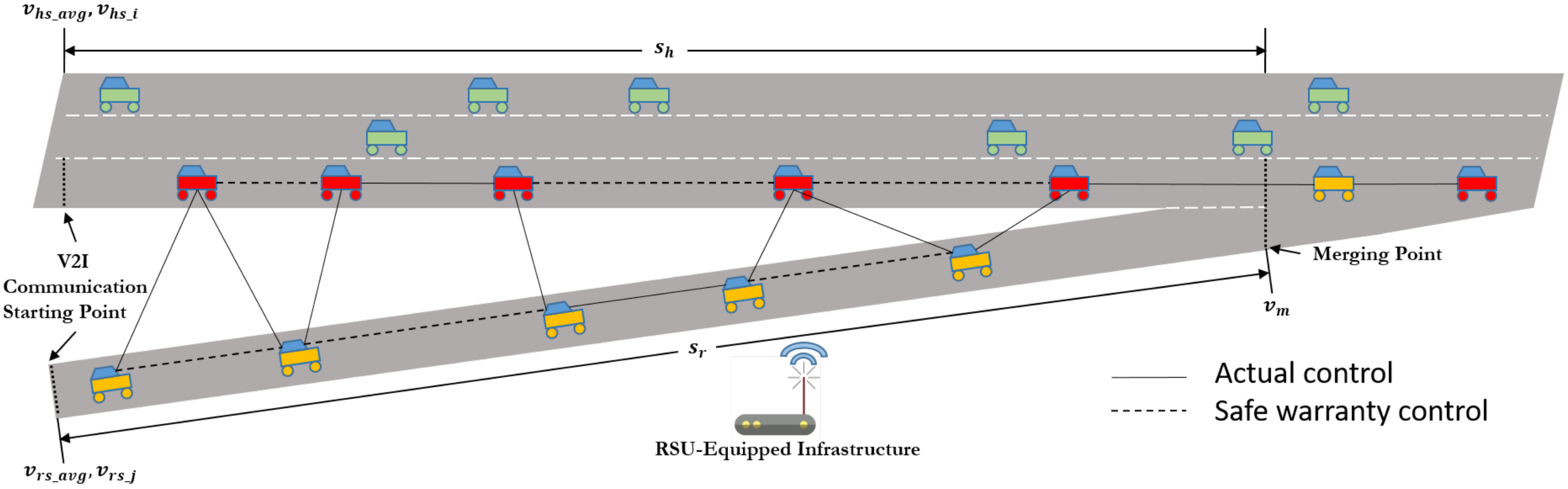
- Safer than human driving by taking a lot of danger out of the equation
- Roadway capacity is increased due to the reduction of inter-vehicle time gap
- Fuel consumption and pollutant emissions are reduced due to the mitigation of unnecessary stop and go, and aerodynamic drag of following vehicles





Cooperative Merging at Highway On-Ramps

- **Cooperative merging at highway on-ramps**
  - **Take advantage of V2V and I2V communication**
  - **Adopt "ghost vehicle" concept**
  - **Complete longitudinal formation before merging**



(Reference: Wang et al, Cooperative ramp merging system: Agent-based modeling and simulation using game engine, SAE International Journal of Connected and Automated Vehicles, 2019)

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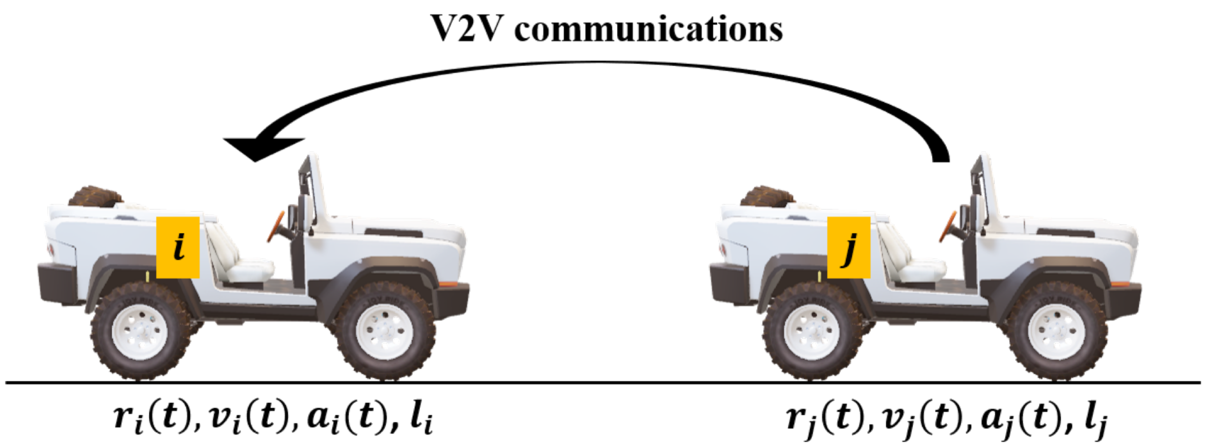
LOOKUP TABLE-BASED CONSENSUS ALGORITHM

Distributed Consensus Algorithms for Car Following



Dynamics of a connected and automated vehicle

$$\dot{r}_i(t) = v_i(t)$$
$$\dot{v}_i(t) = a_i(t)$$

- **First-order consensus algorithm**

$$v_i(t) = -\sum_{j=1}^{n-1} a_{ij}k_{ij}\left(r_i(t) - r_j(t) - gap\right), \qquad i = 2, \dots, n, j = i-1$$

- **Second-order consensus algorithm**

$$a_i(t) = -\sum_{j=1}^{n-1} a_{ij}k_{ij}\left[\left(r_i(t) - r_j(t) - gap\right) + \gamma\left(v_i(t) - v_j(t)\right)\right], \qquad i = 2, \dots, n, j = i-1$$

where a_{ij} is the adjacency matrix of the associated communication graph, k_{ij} and γ are control gains

Distributed Consensus Algorithms for Car Following

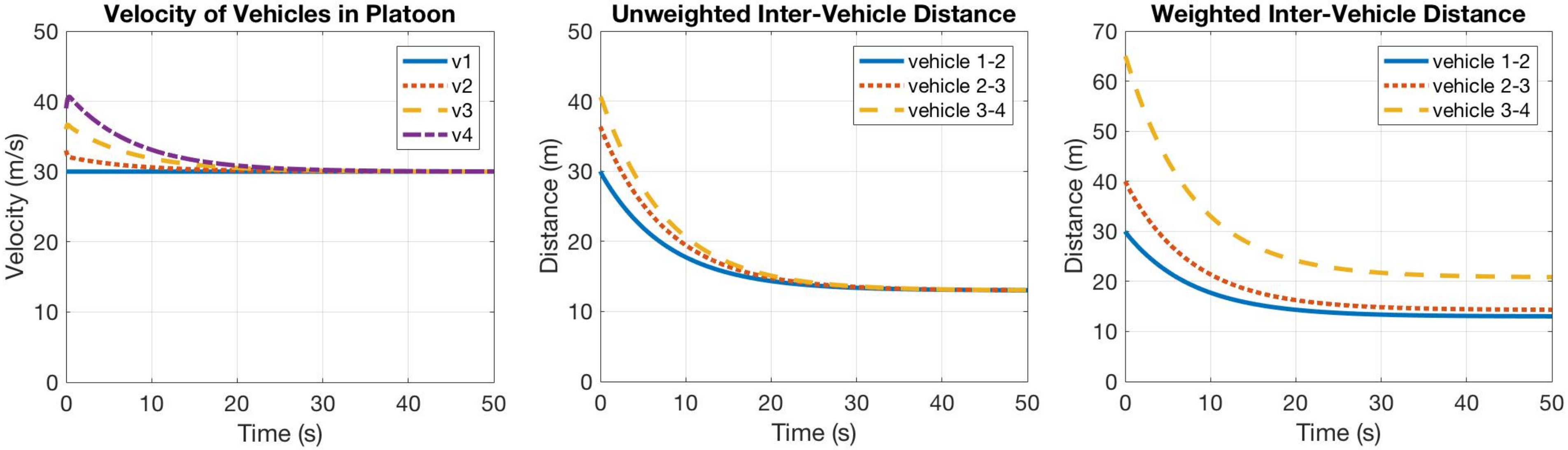
$$\begin{cases} \dot{r}_i(t) = v_i(t) \\ \dot{v}_i(t) = -a_{ij}k_{ij}[r_i(t) - r_j\left(t - \tau_{ij}(t)\right) + l_{if} + l_{jr} + v_i\left(t - \tau_{ij}(t)\right)\left(t_{ij}^g + \tau_{ij}(t)\right)b_i] \\ \qquad -\gamma a_{ij}k_{ij}\left[v_i(t) - v_j\left(t - \tau_{ij}(t)\right)\right] \end{cases}$$

$$i = 2, \ldots, n, j = i - 1$$

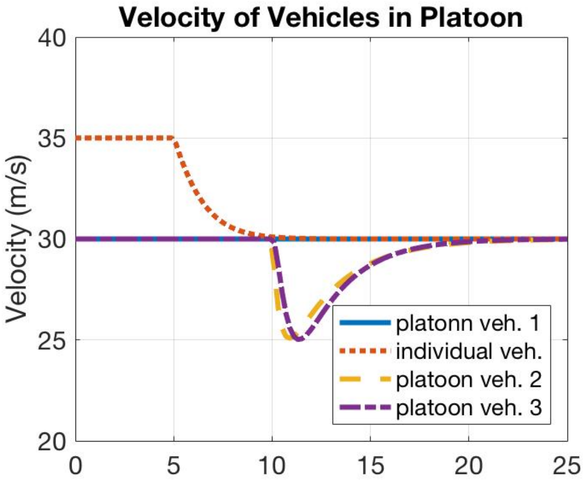
$r_i(t)$	Longitudinal position of vehicle i at time t	t_{ij}^g	Inter-vehicle time gap
$v_i(t)$	Longitudinal speed of vehicle ***i*** at time ***t***	l_{if}	Length between GPS antenna to front bumper
$\dot{v}_i(t)$	Longitudinal acceleration of vehicle ***i*** at time ***t***	l_{jr}	Length between GPS antenna to rear bumper
a_{ij}	(i, j)th entry of the adjacency matrix	b_i	Braking factor of vehicle ***i***
$\tau_{ij}(t)$	Communication delay at time ***t***	γ, k_{ij}	Tuning parameter

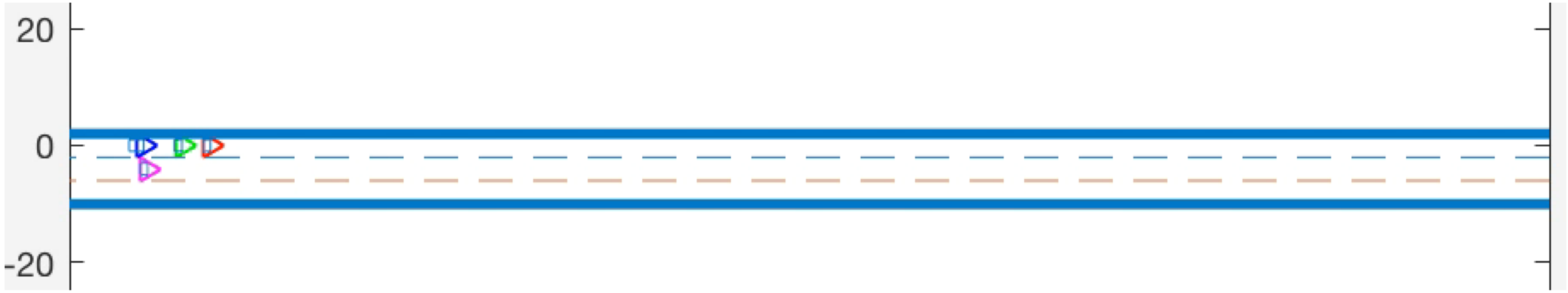
(Reference: Wang et al, Developing a distributed consensus-based CACC for heterogenous vehicles with predecessor-following topology, Journal of Advanced Transportation, 2017)

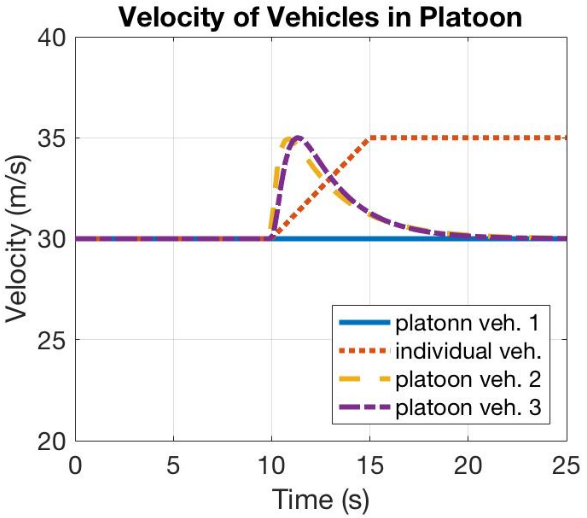
Cooperative Adaptive Cruise Control

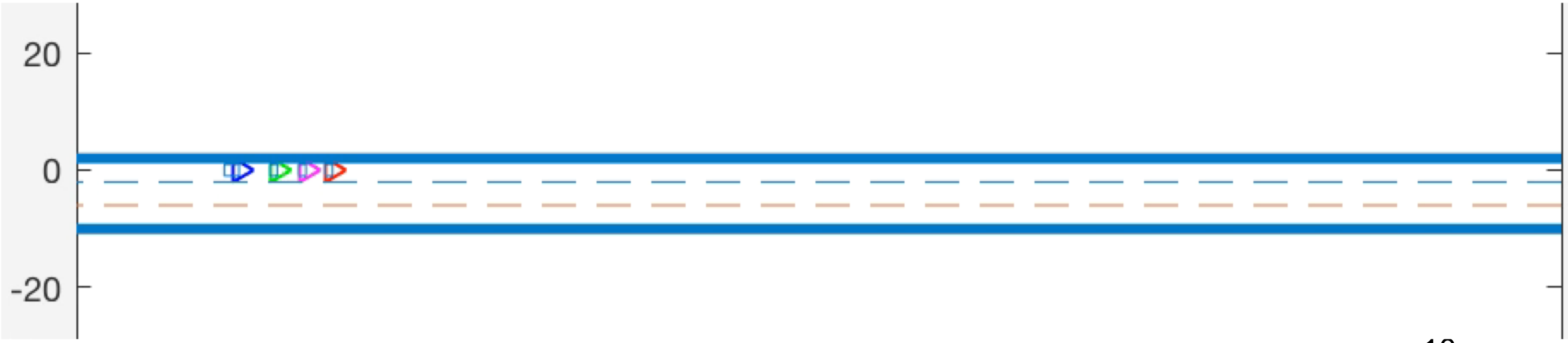


Cooperative Merging and Splitting









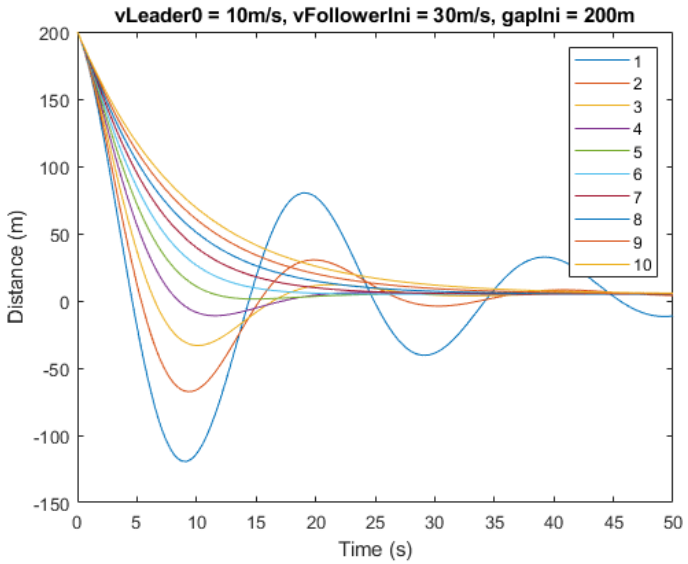
Necessity to Tune Control Gain

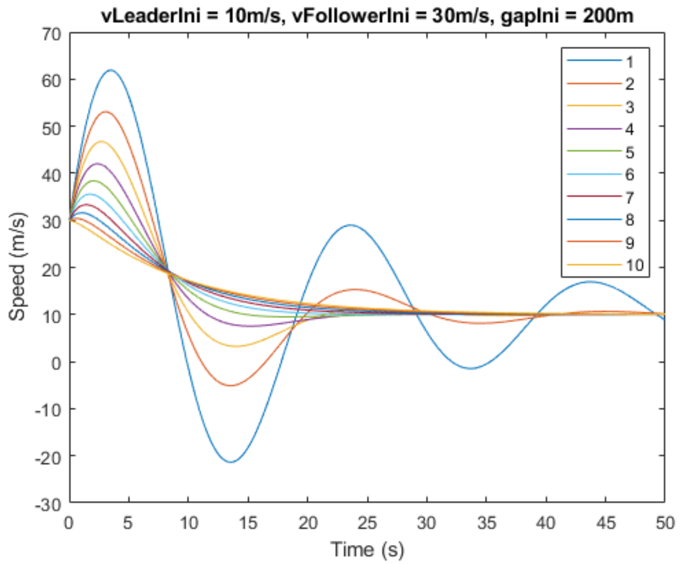
- **Build lookup table for the control gain**

Initial states $\left(\Delta r_{ij}(t_0), v_i(t_0), v_j\left(t_0 - \tau_{ij}(t_0)\right)\right)$ **varies every time the algorithm is switched on by vehicles**

Initial states of vehicles highly affect the convergence of the consensus algorithm

Build up a lookup table to find the suitable value of control gains with respect to different initial conditions





Constraints to Build Lookup Table

Safety Constraint (1st priority)

Evaluated by headway overshoot

$$r_j\left(t-\tau_{ij}(t)\right)-r_i(t)>l_j, t\in[t_0, t_{consensus}]$$

Efficiency Constraint (2nd priority)

Evaluated by convergence time

$$\left|r_j\left(t_{consensus}-\tau_{ij}(t_{consensus})\right)-r_i(t_{consensus})\right|\le\eta_r\cdot\left[l_j+v_i(t_{consensus})\cdot\left(t_{ij}^{g}(t_{consensus})+\tau_{ij}(t_{consensus})\right)\right]$$

$$\left|v_j\left(t_{consensus}-\tau_{ij}(t_{consensus})\right)-v_i(t_{consensus})\right|\le\eta_v\cdot v_j\left(t_{consensus}-\tau_{ij}(t_{consensus})\right)$$

$$|a_i(t_{consensus})|\le\delta_a$$

$$|jerk_i(t_{consensus})|\le\delta_{jerk}$$

Comfort Constraint (3rd priority)

Evaluated by maximum acceleration/deceleration and maximum jerk

$$\Omega_i=\omega_1\cdot\max_{t\in[t_0,t_{consensus}]}(|a_i^{\max}(t)|,|d_i^{\max}(t)|)+\omega_2\cdot\max_{t\in[t_0,t_{consensus}]}\left(|jerk_i^{\max}(t)|,\left|jerk_i^{\min}(t)\right|\right), t\in[t_0, t_{consensus}]$$

Algorithms to Build Lookup Table

Algorithm 1: Build lookup table offline

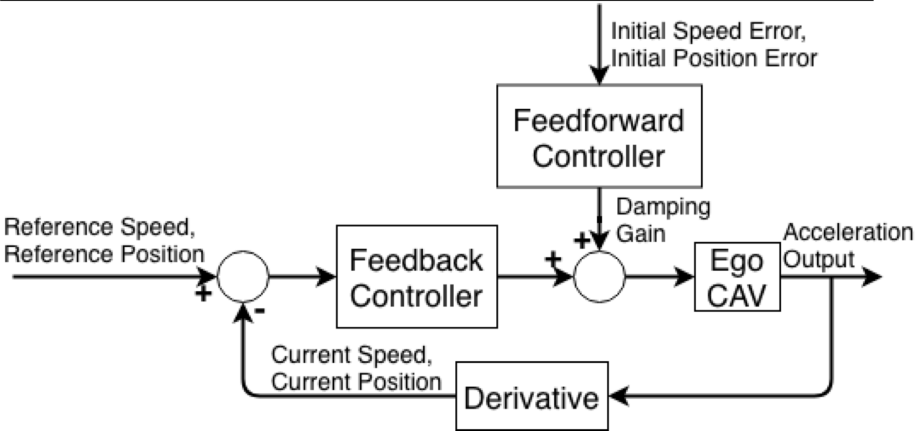
Input: $\Pi_{\Delta r_{ij}} = \left\{\Delta r_{ij_1}, \Delta r_{ij_2}, \dots, \Delta r_{ij_{\zeta 1}}\right\}$, $\Pi_{v_i} = \{v_{i_1}, v_{i_2}, \dots, v_{i_{\zeta 2}}\}$, $\Pi_{v_j} = \{v_{j_1}, v_{j_2}, \dots, v_{j_{\zeta 3}}\}$, $\Pi_{\gamma} = \{v_{\gamma_1}, v_{\gamma_2}, \dots, v_{\gamma_{\zeta 4}}\}$, $\Pi_k = \{v_{k_1}, v_{k_2}, \dots, v_{k_{\zeta 5}}\}$, $\zeta 1 = |\Pi_{\Delta r_{ij}}|$, $\zeta 2 = |\Pi_{v_i}|$, $\zeta 3 = |\Pi_{v_j}|$
Output: 3-dimension table with size $\zeta 1 \times \zeta 2 \times \zeta 3$

for $\xi 1 \in [1, \zeta 1], \xi 2 \in [1, \zeta 2], \xi 3 \in [1, \zeta 3], \Delta r_{ij_{\xi 1}} \in \Pi_{\Delta r_{ij}}, v_{i_{\xi 2}} \in \Pi_{v_i}, v_{j_{\xi 3}} \in \Pi_{v_j}$ **do**
  run algorithm (9) with $\Delta r_{ij_{\xi 1}}$, $v_{i_{\xi 2}}$ and $v_{j_{\xi 3}}$
  find $\Lambda_\gamma \subseteq \Pi_\gamma, \Lambda_k \subseteq \Pi_k$ satisfy *Constraint 1*
  if $\Lambda_\gamma = \emptyset \,||\, \Lambda_k = \emptyset$ **then**
    $\gamma_{(\xi 1, \xi 2, \xi 3)} = NaN,\ k_{(\xi 1, \xi 2, \xi 3)} = NaN$
  else
    find $\Psi_\gamma \subseteq \Lambda_\gamma, \Psi_k \subseteq \Lambda_k$ satisfy *Constraint 2*
    if $|\Psi_\gamma| == |\Psi_k| == 1$ **then**
      $\gamma_{(\xi 1, \xi 2, \xi 3)} \in \Psi_\gamma, k_{(\xi 1, \xi 2, \xi 3)} \in \Psi_k$
    else
      find $\Phi_\gamma \subseteq \Psi_\gamma, \Phi_k \subseteq \Phi_k$ satisfy *Constraint 3*
      if $|\Phi_\gamma| == |\Phi_k| == 1$ **then**
        $\gamma_{(\xi 1, \xi 2, \xi 3)} \in \Phi_\gamma, k_{(\xi 1, \xi 2, \xi 3)} \in \Phi_k$
      else
        $\gamma_{(\xi 1, \xi 2, \xi 3)} = \min_{\gamma \in \Phi_\gamma} \Phi_\gamma, k_{(\xi 1, \xi 2, \xi 3)} = \min_{k \in \Phi_k} \Phi_k$
      end if
    end if
  end if
end for

Algorithm 2: Search lookup table in real time

Input: $\left(\Delta r_{ij}(t_0), v_i(t_0), v_j\left(t_0 - \tau_{ij}(t_0)\right)\right)$, $(\zeta 1 \times \zeta 2 \times \zeta 3)$ size of lookup table
Output: values of control gains k and γ

for $\Delta r_{ij}(t_0), v_i(t_0), v_j\left(t_0 - \tau_{ij}(t_0)\right)$ **do**
  if $\Delta r_{ij}(t_0) < \Delta r_{ij_1} || \Delta r_{ij}(t_0) > \Delta r_{ij_{\zeta 1}} || v_i(t_0) < v_{i_1} || v_i(t_0) > v_{i_{\zeta 2}} || v_j\left(t_0 - \tau_{ij}(t_0)\right) < v_{j_1} || v_j\left(t_0 - \tau_{ij}(t_0)\right) > v_{j_{\zeta 3}}$ **then**
    return $\gamma = NaN,\ k = NaN$
  else
    find $\left(\Delta r_{ij_{\xi 1}} \middle| \min \left|\Delta r_{ij}(t_0) - \Delta r_{ij_{\xi 1}}\right|\right)$, $\left(v_{i_{\xi 2}} \middle| \min \left|v_i(t_0) - v_{i_{\xi 2}}\right|\right)$, $\left(v_{j_{\xi 3}} \middle| \min \left|v_j\left(t_0 - \tau_{ij}(t_0)\right) - v_{j_{\xi 3}}\right|\right)$
    return $\gamma = \gamma(\Delta r_{ij_{\xi 1}}, v_{i_{\xi 2}}, v_{j_{\xi 3}}), k = k\left(\Delta r_{ij_{\xi 1}}, v_{i_{\xi 2}}, v_{j_{\xi 3}}\right)$
  end if
end for



Numerical Simulation Results

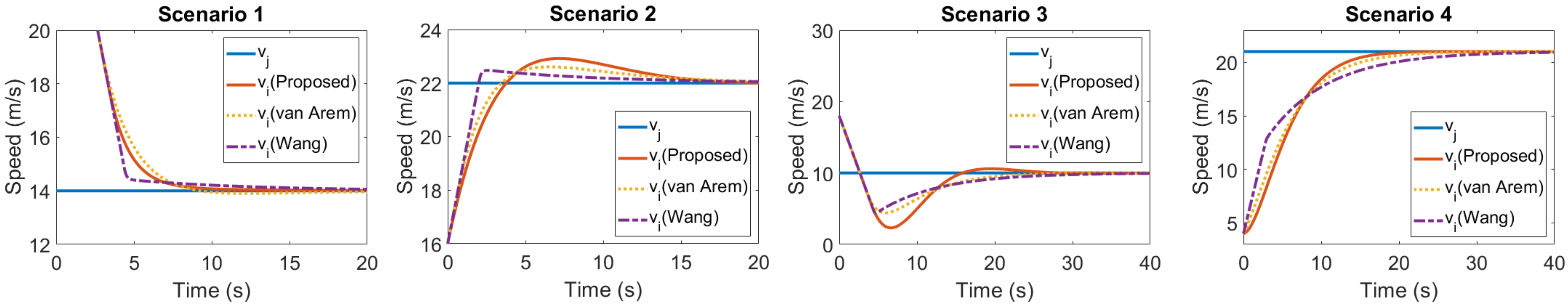
- **Compare to our existing algorithm, as well as van Arem's CACC algorithm**

TABLE I. Settings of Simulation Scenarios

	$\Delta r_{ij}(t_0)$ (m)	$v_i(t_0)$ (m/s)	$v_j\left(t_0 - \tau_{ij}(t_0)\right)$ (m/s)
Scenario 1	50	28	14
Scenario 2	20	16	22
Scenario 3	-30	18	10
Scenario 4	-80	4	21

TABLE II. SIMULATION RESULTS

	Convergence time (s)				Maximum jerk (m/s^3)			
Scenario	1	2	3	4	1	2	3	4
Wang	35.9	35.0	56.5	57.6	21.2	20.7	25.7	13.4
van Arem	29.3	32.1	41.8	40.1	1.5	1.6	2.3	0.7
Proposed	24.9	22.9	32.1	28.3	2.3	0.8	1.6	1.6



FUTURE WORK AND ACKNOWLEDGEMENT

Future Work

- Build a more comprehensive lookup table especially when leading vehicle's speed is dynamically changing
- Consider higher-order vehicle dynamics to consider acceleration and jerk of the leading vehicle
- Test the effectiveness of the proposed methodology in various real-world traffic scenarios

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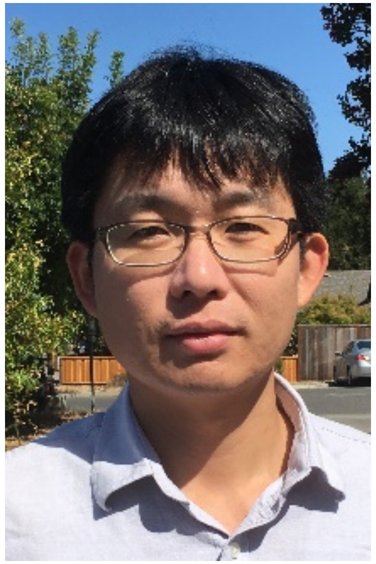
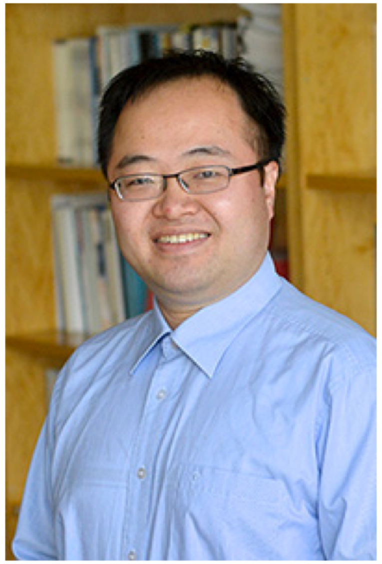
Acknowledgement

				
Ziran Wang **http://ziranw.github.io**	**Kyungtae Han** **Principal Researcher**	**BaekGyu Kim** **Principal Researcher**	**Guoyuan Wu** **Adjunct Professor**	**Matthew Barth** **Professor**

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Thank you all! QUESTIONS?