Enabling System Level Functionality for Autonomous Vehicles

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1. Research Objectives

Transportation systems are ever evolving dynamic and complex. Self-driving vehicles are becoming more powerful and rapidly infiltrating the global market. As such, a new dimension of complexity is disrupting our transportation systems, one that comes from heterogeneity in behavior, performance, and design. This culmination of research efforts focuses on guiding the design of emerging transportation technologies in ways that are not myopic but consider system level performance.

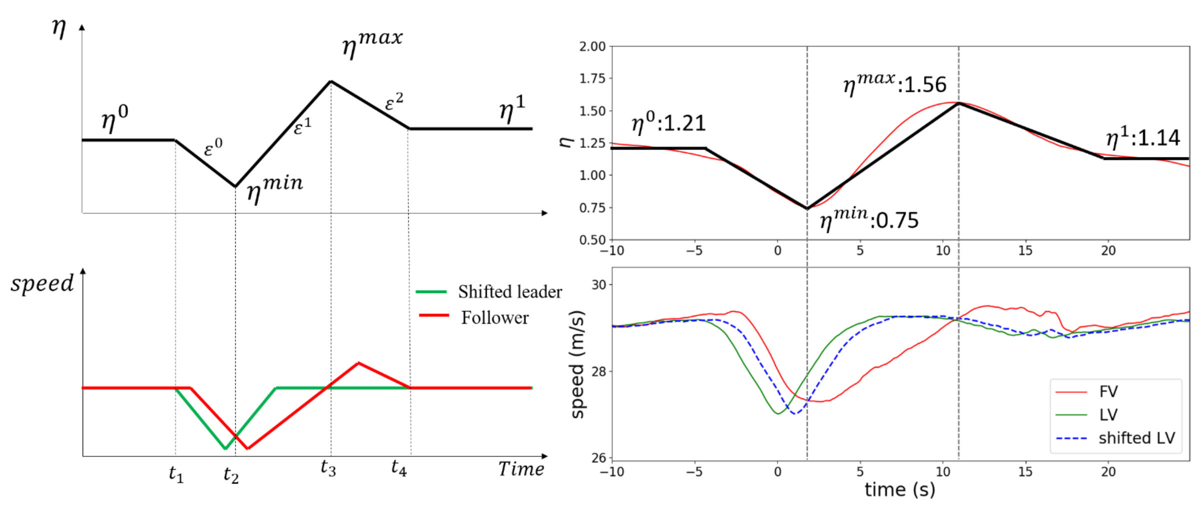
i. Analytical and empirical investigation of control algorithms for commercially available automated vehicles
ii. Implications of control design on traffic and system dynamics
iii. Real-time dynamic control to preserve desired system level performance
iv. Moving from IoT into IoFT (Internet of Federated Things)

2. Commercial Control Algorithms for Automated Vehicles

I. A Unifying Model for Analysis

Propriety rights of commercial automated vehicles (AVs) hinders the ability of researchers to analytical investigate their impact on a traffic system dynamic. Consequently, we design and empirically sustain the use of a physics-based Asymmetric Behavioral (AB) model that can (i) serve as a unifying framework to analyze different control paradigms (ii) capture key characteristics related to traffic dynamics. In here we focus on car-following behavior.

$$y_i(t) = y_{i-1}(t - \eta_i(t)\tau) - \eta_i(t)\delta$$



II. From Control Design to Control Mechanisms

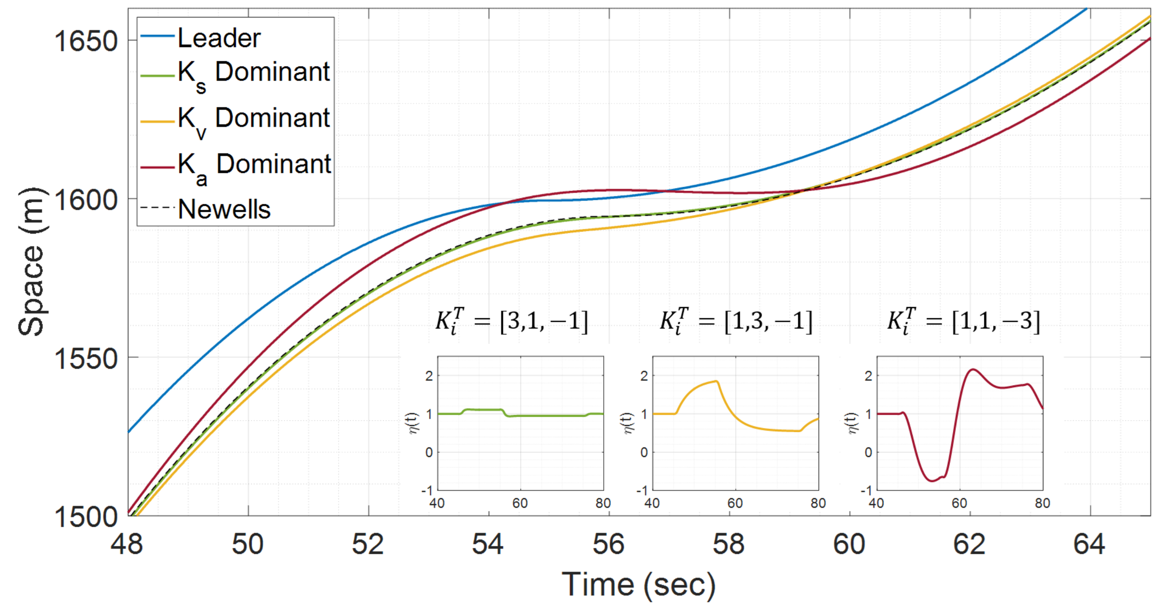
An autonomous vehicles controller regulates the vehicle's system state $\boldsymbol{x}_i(t) = [\Delta d_i(t), \Delta v_i(t), a_i(t)]^T$ through the demanded acceleration $u_i(t) = \boldsymbol{K}^T x_i(t)$. Where $\Delta d_i(t)$ is the deviation from desired spacing, $\Delta v_i(t)$ is the relative speed, and $a_i(t)$ is the vehicle acceleration. Where $\boldsymbol{K}^T = [k_s, k_v, k_a]$ is a vector of control gains regulating each system state.

The developed unifying model provides a unique opportunity to translate AV control mechanisms into system level behavior and assess different implications.

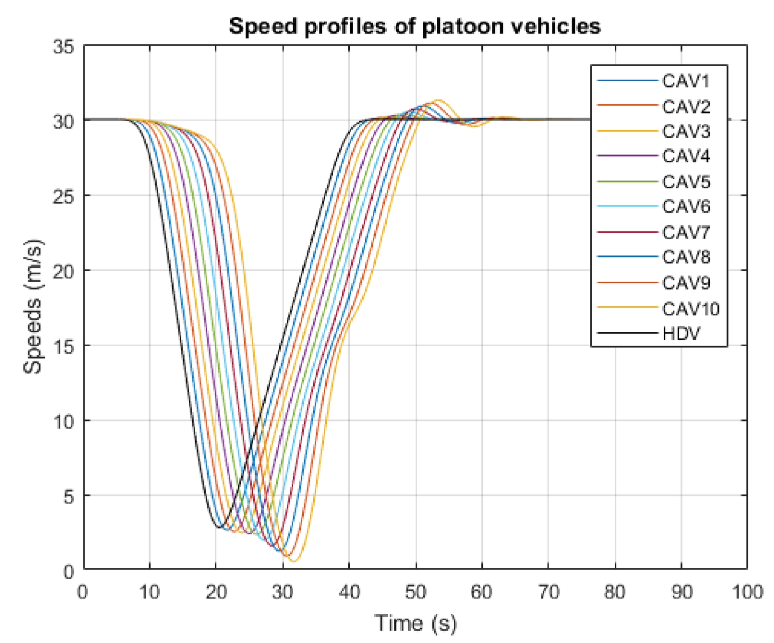
III. System Level Implications of Control Design

While commercial controllers focus on maximizing their own utility (safe and optimal microscopic behavior), their design has systematic implications on the system itself. The commands triggered by the controller and the magnitude of each creates complexities in behavior and system dynamics.

K_i	Coefficient	Controller Command	Effect of $\lvert k_i \rvert \uparrow$
k_s	$\Delta d_i(t)$	Maintain the target spacing	Pushes towards neutral behavior (constant pattern)
k_v	$\Delta v_i(t)$	Match the leader's speed	Generates responsive behavior (concave-convex pattern)
k_a	$a_i(t)$	Minimize acceleration	Resists acceleration change (convex-concave pattern)



It is noted that the controller design has a significant impact on the system and traffic stability. Investigations on commercial AVs showed that they are string unstable, meaning that they magnify amplitude of disturbances along the traffic system.



3. Preserving Desired System Level Performance for Autonomous Vehicles

I. Real-time Approach to System Level Performance

Along with control gains – which are pre-defined parameters – it was found that stochastic parameters such as actuation lag (T_L) and ratio of realized acceleration (K_L) have profound impact on control behavior and thus system dynamics. We thus take a real-time approach to estimate stochastic uncertainties in key parameters as to gain insights into internal errors in control as a result of real-world dynamics.

$$\nabla(K_L^t, T_L^t) = \frac{\eta_t}{2}\left(\nabla \log P(K_L^t, T_L^t) + \frac{N_{\tilde{t}}}{n}\sum_{i=1}^{n} \nabla \log P(\dot{a}_i | a_i, u_i, K_L^t, T_L^t)\right) + \varepsilon_t$$

$$\varepsilon_t \sim \mathcal{N}(0, \eta_t \boldsymbol{I})$$

II. Online Algorithm for System Level Control Adjustments

Given our knowledge on control mechanisms, its impact on vehicle behavior and system dynamics. We build an online algorithm that aims at: (i) monitoring the deviation of vehicle from desired state, (ii) analyzing the impact of this shift on system dynamics, (iii) update and adjust controller so that system level performance is realized.

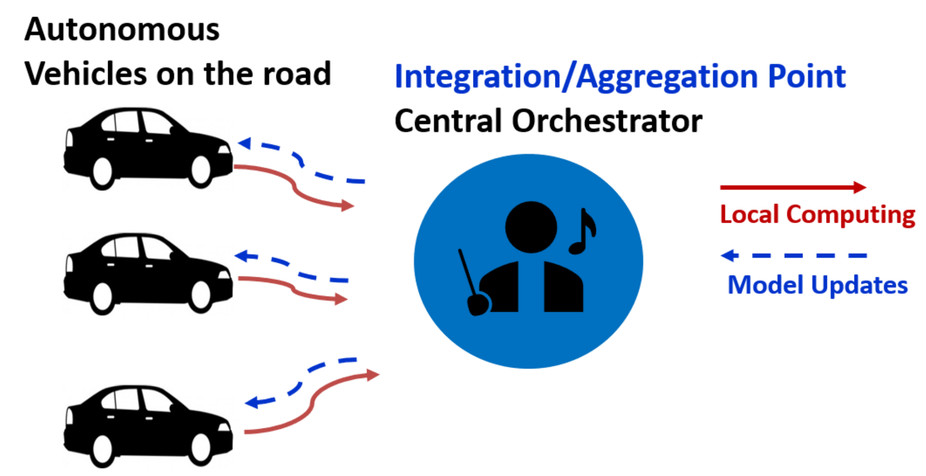
Algorithm 1: Online Strategy: Pseudo Code

Input: Parameter estimates $\theta^{(t)} = \left[K_L^{(t)}, T_L^{(t)}\right]$
if $\theta^{(t)} \neq [K_L, T_L]$ **then**
  Check stability (local and string)
  if *Stable* **then**
    Update lower-level controller: $[K_L, T_L] \leftarrow \left[K_L^{(t)}, T_L^{(t)}\right]$
  end if
  if *Unstable* **then**
    Update upper-level controller:
      1. Update Control gains: $\left[|k_s'| > |k_s|, |k_v'| > |k_v|, |k_a'| < |k_a|\right]^\top \leftarrow [k_s, k_v, k_a]^\top$
      2. Update time gap: $\tau^{*'} < \tau^* \leftarrow \tau^*$
  end if
end if

4. The Internet of Federated Things (IoFT)

I. Harnessing the Computational Power of Edge Devices

In order to realize the system level functionality of AVs it is critical to achieve a level of collaboration in adjusting vehicle behavior to maintain a desired system performance. This however necessitates (i) immense communication efforts, (ii) privacy interactions, (iii) complexity in computation and (iv) negligible computational latency. Thus, we envision the movement from IoT into IoFT where the "Cloud" is substituted by the "Crowd"



Assume N vehicles, the goal of Federated Learning (FL) in IoFT is to collaboratively learn a global model f_w parametrized by w

$$\min_w F(w) := \frac{1}{N}\sum_{i=1}^{N} F_i(w)$$

Where $F_i(w)$ is a risk function defined as

$$F_i(w) = \mathbb{E}_{(x_i, y_i) \sim D_i}[\ell(f_w(x_i), y_i)] \approx \frac{1}{n_i}\sum_{j=1}^{n_i}[\ell(f_w(x_i), y_i)]$$

In IoFT, vehicle i can only evaluate its own risk function $F_i(w)$ and orchestrator has no access to client datasets D_i