On Multi-class Automated Vehicles: Car-following Behavior and Its Implications for Traffic Dynamics

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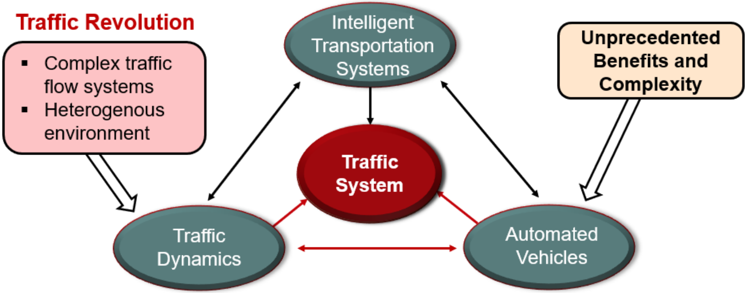
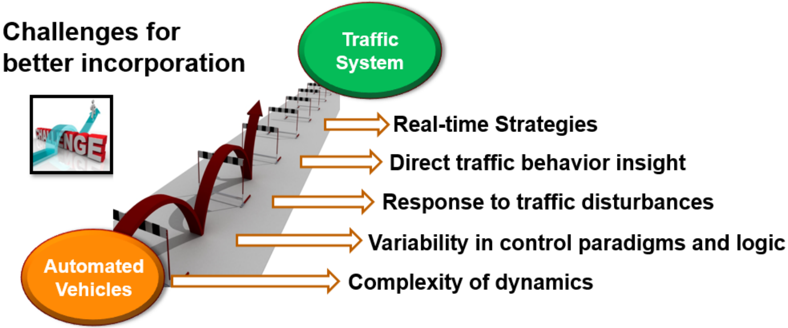
The New Traffic Environment

- Complexity of behavior is redefining the traffic system.



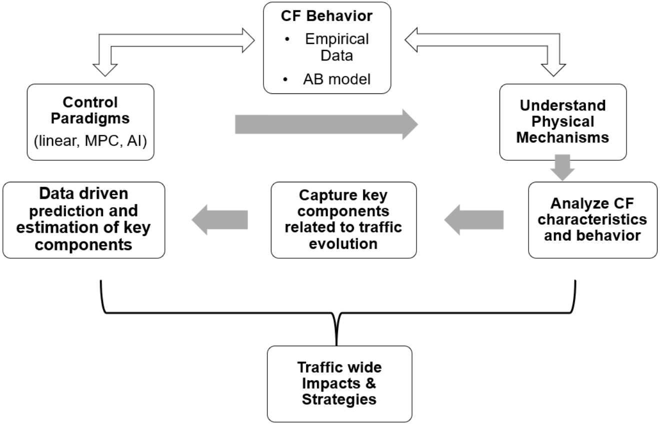
Challenges



- To realize the full potential of AVs and incorporate them into our traffic systems, an analysis into the nature and dynamics of behavior is needed

Research Objectives

- Characterize Car-following (CF) behavior of multi-class AVs under different control paradigms and parameter settings
- Translate microscopic control paradigms into aggregate traffic-level dynamics



Part I: CF Mechanisms of Multi-class AVs

The Asymmetric Behavioral (AB) Model

Principal Idea [1, 4]

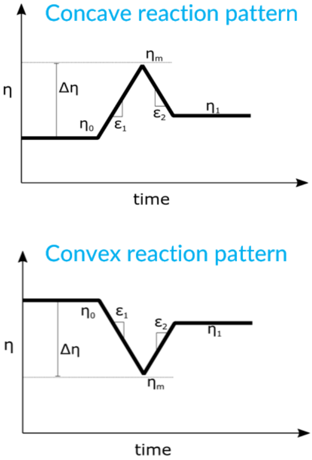
Physics-based CF model, an extension of Newell's: Vehicle's temporal deviation in time gap (τ) or constant minimum spacing (δ) from its equilibrium position as defined by Newell, expressed through parameter $\eta_i(t)$

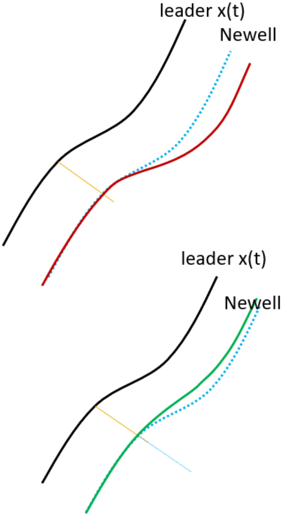
$$y_i(t) = y_{i-1}(t - \eta_i(t)\tau) - \eta_i(t)\delta \quad (1)$$

where y_i and y_{i-1} are the positions of vehicle i and its leader $i-1$

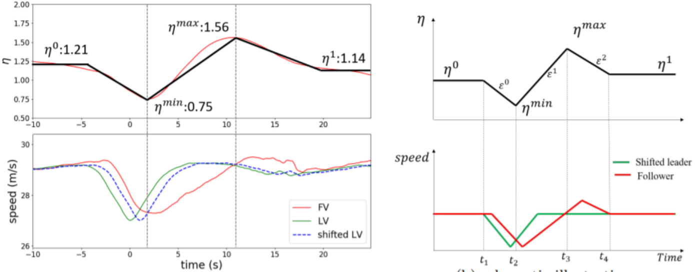
$\eta(t)$: Highlights key aggregate characteristics and trends that influence the disturbance propagation (magnitude, direction and duration of different phases, reaction to the leader trajectory)

Reaction Patterns of AB Model: $\eta(t)$ [1]





Adaptive Cruise Control Empirical Data: Observations of AB Reaction Patterns [2, 3]



(a) observed evolution

(b) schematic illustration

- Reaction patterns of AB model ($\eta(t)$ evolution) can capture can capture main characteristics of controller design and explain the governing physical behavior

Part II: Physical Insights of AV's CF Mechanisms

Main Insight

Control parameter setting and overall logic translates into the $\eta(t)$ profile of the AB model, allowing us to gain insights into the range of CF behavior possible and its impact on disturbance evolution

Analysis of Linear Controller

Linear Feedback Control Structure: Regulate the AV's acceleration to follow a pre-defined equilibrium spacing. The system state is described by: $\boldsymbol{x}_i(t) = [\Delta d_i(t), \Delta v_i(t), a_i(t)]^T$ [5]

- Deviation of actual spacing from equilibrium spacing: $\Delta d_i(t) = d_i(t) - d_i^*(t)$
- Speed difference between leader and follower: $\Delta v_i(t) = v_{i-1}(t) - v_i(t)$
- Acceleration: $a_i(t)$

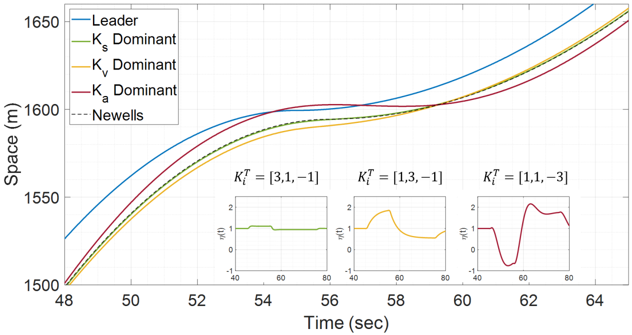
The control input $u_i(t)$ is then formulated as:

$$u_i(t) = \boldsymbol{K}_i^T \boldsymbol{x}_i(t), \boldsymbol{K}_i^T = [k_{si}, k_{vi}, k_{ai}] \tag{2}$$

- k_s: Feedback gain for the deviation from equilibrium spacing
- k_v: Feedback gain for the speed difference
- k_a: Feedback gain for the acceleration

$\boldsymbol{K}_i^T$ denotes the regulation magnitude for each component; **governs the CF behavior**

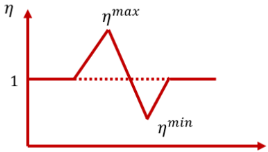
Effect of each control gain on CF behavior and $\eta(t)$ profile.



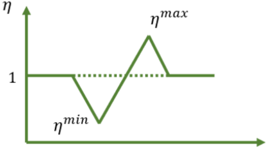
K_i	Coefficient	Controller Command	Effect of $\lvert k_i \rvert \uparrow$
k_s	$\Delta d_i(t)$	Maintain the target spacing	Pushes towards Newell behavior (constant pattern)
k_v	$\Delta v_i(t)$	Match the leader's speed	Generates responsive behavior (concave-convex pattern)
k_a	$a_i(t)$	Minimize acceleration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

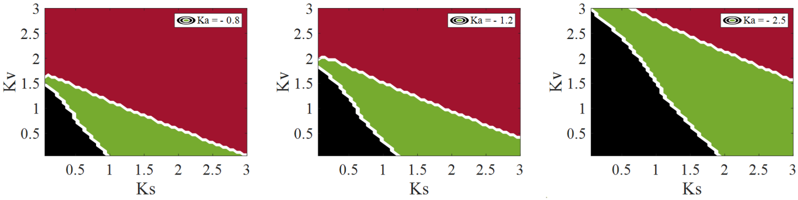
Mapping Control Gains to Reaction Patterns

Concave-Convex

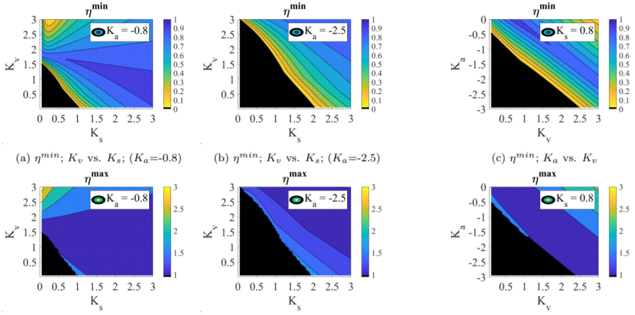


Convex-Concave





Mapping Control Gains to AB Model Parameters (η^{min}, η^{max})



(a) η^{min}; K_v vs. K_s; (K_a=-0.8) (b) η^{min}; K_v vs. K_s; (K_a=-2.5) (c) η^{min}; K_a vs. K_v

(d) η^{max}; K_v vs. K_s; (K_a=-0.8) (e) η^{max}; K_v vs. K_s; (K_a=-2.5) (f) η^{max} mapping; K_a vs. K_v

- (η^{min}, η^{max}) and k_s: monotonic relationship
- (η^{min}, η^{max}) and k_v and k_a: non-monotonic relationship
- Comparative strength of k_a and k_v determines reaction pattern, while k_s dampens the reaction

Analysis of Model Predictive Controller (MPC)

MPC Formulation [6]:

- similar system state: $\boldsymbol{x}_i(t) = [\Delta d_i(t), \Delta v_i(t), a_i(t)]^T$
- Running cost function at each time step of prediction horizon given as:

$$\sum_{m=1}^{k_p} L_i(x^{p,k}_{i,k+m}, u^{p,k}_{i,k+m-1}) = (x^{p,k}_{i,k+m})^T Q_i(x^{p,k}_{i,k}) + R_i(u^{p,k}_{i,k+m-1})^2 \quad (3)$$

$$\begin{aligned} a_{i,min} \leq H x^{p,k}_{i,k} \leq a_{i,max} \\ \Delta d_i^- \leq G x^{p,k}_{i,k} \leq \Delta d_i^+ \end{aligned} \quad (4)$$

$Q_i = \begin{bmatrix} \alpha_{1,i} & & \\ & \alpha_{2,i} & \\ & & \alpha_{3,i} \end{bmatrix}$; and R_i is a scalar; $(a_{i,min}, a_{i,max})$ are the deceleration and acceleration constraints, respectively; $(\Delta d_i^-, \Delta d_i^+)$ depict the maximum allowable deviations from target spacing.

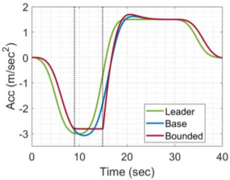
Analysis of Control Mechanisms and CF Behavior

Impact of weight matrix Q_i

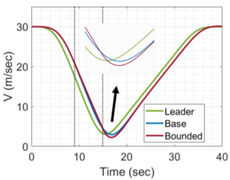
Similar functionality is observed to that of $\boldsymbol{K}^T$ of the linear controller. Analogously: $\alpha_1 :\equiv k_s$; $\alpha_2 :\equiv k_v$; $\alpha_3 :\equiv k_a$. Accordingly, when α_1 is dominant we observe Newell-like behavior, dominant α_2 leads to concave-convex reaction pattern, and dominant α_3 leads to a convex-concave reaction pattern.

Effects of bounded deceleration:

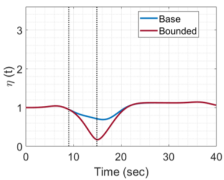
- Significant convexity: follower closes in sharply into the leader
- Unstable control: minimum speed decreases
- Jerk increases: transition from deceleration into acceleration is faster



(a) Acceleration profile



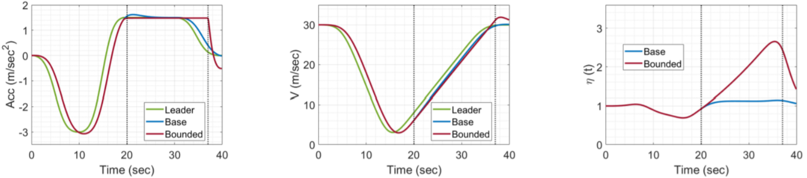
(b) Speed profile



(c) $\eta(t)$

Effects of bounded acceleration:

- Significant concavity: increase in gap and prolonged recovery
- Overshoot in speed: to close the extra gap



(a) Acceleration profile

(b) Speed profile

(c) $\eta(t)$

Part III: Predictive Modeling for Car-following Behavior

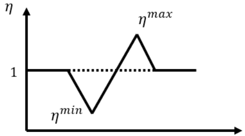
Predictive Modeling

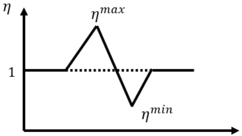
Control logic and parameter setting results in unique $\eta(t)$ evolution, characterized by its shape and parameter values $\left(\eta^{min}, \eta^{max}\right)$.

Given control parameter setting (e.g., $\boldsymbol{K}_i^T$, Q_i) and a leader oscillation information, we can predict the AV behavior via $\eta(t)$ profile.

Bi-level prediction modeling framework:

- Classification model: predicts $\eta(t)$ reaction pattern
- Multivariate Convoluted Gaussian Process ($\mathcal{MGP}$): predict $\left(\eta^{min}, \eta^{max}\right)$





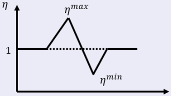
Part IV: Traffic Level Implications

Linear Controller

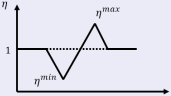
Lessons Learned

1) Stability:

- Concave-Convex reaction pattern results in stable traffic: allows for disturbance dampening



- Convex-Concave reaction pattern results in unstable traffic: amplification of disturbances



Part IV: Traffic Level Implications

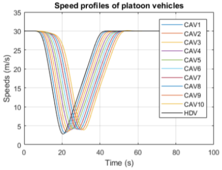
Lessons Learned

2) Vehicle ordering impact:

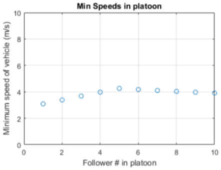
- Vehicle ordering affects how the disturbance magnitude (speed reduction) evolves from vehicle to vehicle. However, the average behavior (based on minimum speed and time to reach equilibrium for the final vehicle in the platoon) is independent of ordering.

Part IV: Traffic Level Implications

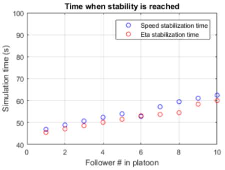
AVs from single class (same reaction pattern) congregate together



(a) Speed profile

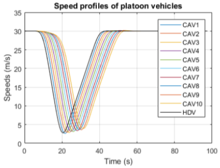


(b) Minimum speeds

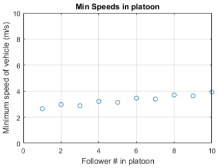


(c) Time to reach equilibrium

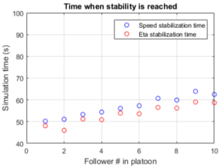
AVs from different classes (different reaction patterns) intermingle.



(d) Speed profile



(e) Minimum speeds



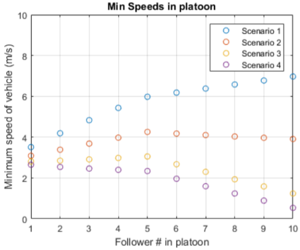
(f) Time to reach equilibrium

Part IV: Traffic Level Implications

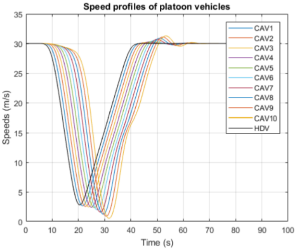
Lessons Learned

3) Impact of platoon composition (different parameter settings) on disturbance evolution:

- Control settings that fall within the concave-convex (convex-concave) reaction region are expected to result in disturbance dampening (amplification)
- In settings of disturbance amplifications various extends of speed overshooting is observed (extending the recovery time)



(a) Platoon min. speeds - All 4 scenarios



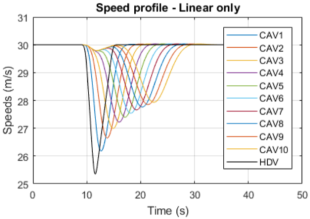
(b) Speed profile - Scenario 4

MPC Controller

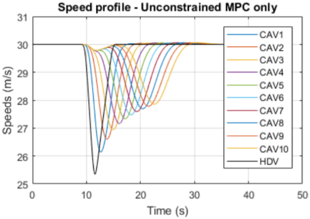
Lessons Learned

1) Unconstrained scenarios

- When MPC is unconstrained, the behavior is similar to that seen linear controller (with equivalent control parameter settings)



(a) Linear controller platoon



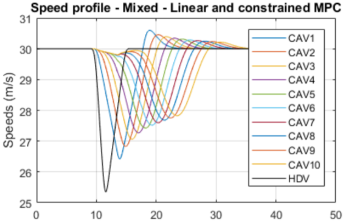
(b) Unconstrained MPC platoon

Part IV: Traffic Level Implications

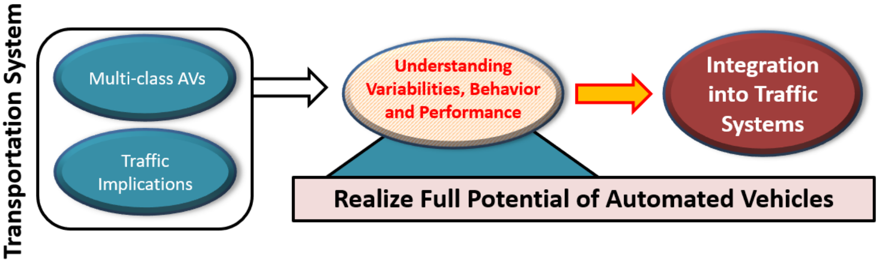
Lessons Learned

2) Constrained scenarios

- Constraints become limiting only for first MPC vehicle in the platoon (subsequent vehicles never reach constraint conditions) - Note here constraints are weak
- Active constraints would result in an increase in disturbance duration, possibly with a secondary one being created
- Enough vehicles with active constraints may lead to overall disturbance amplification, even if weight parameters are set for string stability



Conclusions and Summary of Contribution



Thank You

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