Anomaly Detection and String Stability Analysis in Connected Automated Vehicular Platoons

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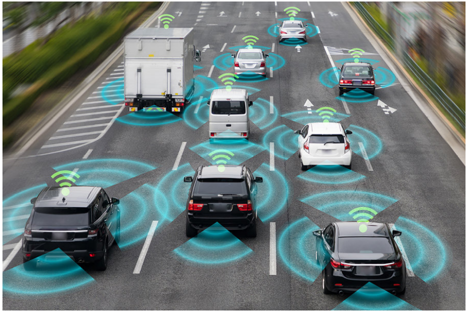
Agenda

- Introduction and Motivation
- Solution Methodology
- Experimental Results
- Conclusion

Background

- Transportation system becomes smarter and more connected
  - Development of communication technologies, ML, DL
- CAV technology can improve performance of ITS
  - Decrease fatal traffic crashes by 80%, reduce 6.9 billion hours (USDOT, 2016)
  - Improve fuel economy and traffic stability (Jin & Orosz, 2014; Sun, 2020)



Source: https://www.tataelxsi.com/industries/automotive/c-a-s-e

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Concerns

- Increasing levels of connectivity & automation $\longrightarrow$ multiple attack surfaces
  - Internal surfaces: OBD, LiDAR, etc. (Cao et al., 2019)
  - External surfaces: RSU, Communications, etc. (Feng et al., 2018)
- Uncertainties on measurements
  - noises, time delay, etc.

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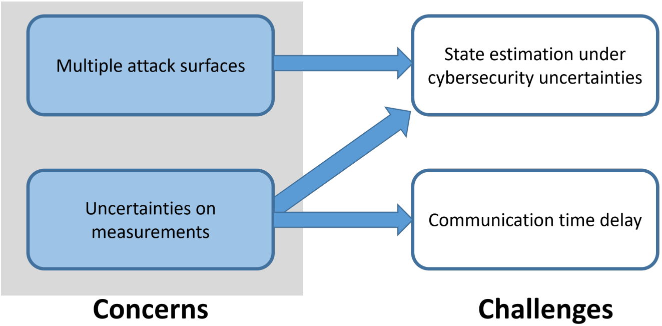
Challenges



- Presence of anomalies: Sensor faults, malicious attack
- Presence of measurement noises: Communication white noise, sensor noise

- Jamming attack, bandwidth limit, etc.

Motivation and Objective

- Motivation
  - More attack surfaces on CAVs
  - CAV can utilize multiple vehicles' information

- Objective
  - Secure CAV sensor state estimation
  - Attack/anomaly detection
  - Platoon string stability analysis under cybersecurity uncertainties

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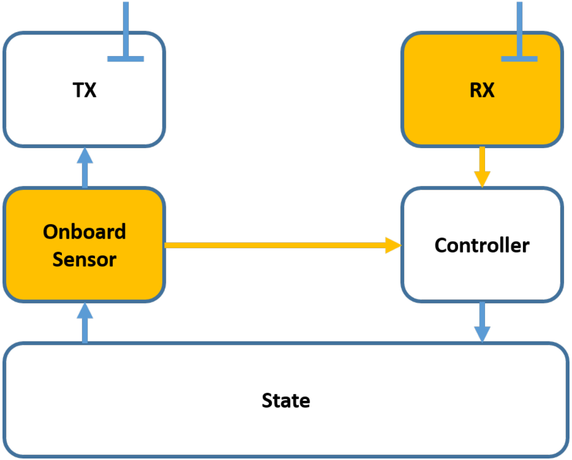
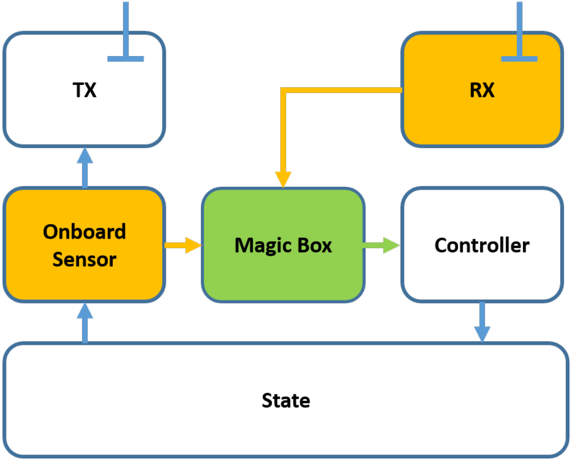
Methodology

CAV System



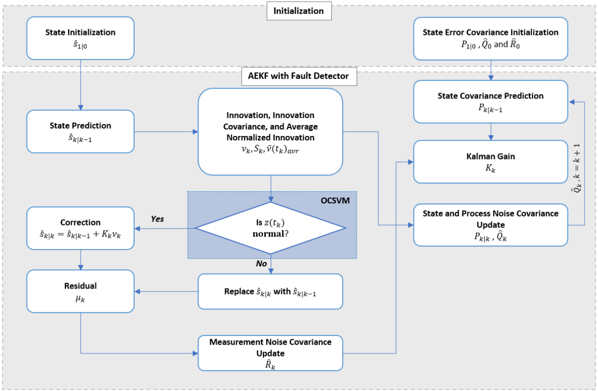
Magic Box



Inside the Box

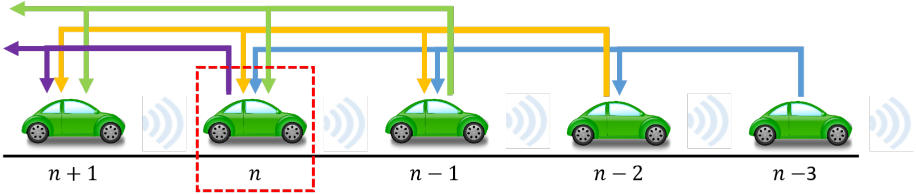
Signal Filtering + Detector:

- Construct state-space model of vehicle's motion
- Estimate unknown variables from noisy measurements under time delay
- Detect anomalies based on innovation (residual)



Assumption

- Vehicles are under a platooning mode
- Heterogeneous time delay applied to the inputs:
  - τ_1 in onboard measurement
  - τ_2 in communication channel
- Anomalies come from either sensor faults, or from an attacker who conducts false injection attack on sensor measurement trying to cause a wrong estimation of state variables
- Bounded acceleration of each vehicle



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Construct State-Space Model

Extended version of platoon model in (Wang et al., 2020a):

$$\dot{v}_n(t) = f(\underbrace{v_n(t-\tau_1)}_{\text{velocity of ego vehicle}}, \overbrace{\bar{g}_n(t;\tau_1,\tau_2)}^{\text{weighted sum of clearance gap}}, \underbrace{\bar{d}_n(t;\tau_1,\tau_2)}_{\text{weighted sum of relative velocity}}) \tag{1}$$

where

$$\bar{g}_n(t;\tau_1,\tau_2) := \alpha_1 \overbrace{w_1(t-\tau_1)}^{\text{adjacency variable}} \underbrace{g_n(t-\tau_1)}_{\text{clearance gap}} + \sum_{j=2}^{M} \alpha_j \overbrace{w_j(t-\tau_2)}^{\text{adjacency variable}} \underbrace{g_{n-j+1}(t-\tau_2)}_{\text{clearance gap}}$$

$$\bar{d}_n(t;\tau_1,\tau_2) := \beta_1 w_1(t-\tau_1) \underbrace{\Delta v_n(t-\tau_1)}_{\text{relative velocity}} + \sum_{j=2}^{M} \beta_j \left(w_j(t-\tau_2)\right) \underbrace{\Delta v_{n-j+1}(t-\tau_2)}_{\text{relative velocity}}$$

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Construct State-Space Model Cont.

- Augmented state vector $\tilde{s}(t) = [x_n(t), v_n(t), \sigma_n(t)]^T$
- Input vector $u(t; \tau_1, \tau_2) := [\bar{g}_n(t; \tau_1, \tau_2), \bar{d}_n(t; \tau_1, \tau_2)]^\mathsf{T}$

Continuous-time state-transition model with discrete-time measurement,

$$\begin{aligned} \dot{\tilde{s}}_n(t) &= \mathcal{T}(s_n(t - \tau_1), u_n(t; \tau_1, \tau_2)) + \theta(t) \\ z_n(t_k) &= \mathcal{M}(s_n(t_k)) + \eta(t_k), \;\; k \in \{0 \cup \mathbb{Z}^+\} \end{aligned} \tag{2}$$

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Stochastic Time Delay

Consider the linear model of $\tilde{\tau}_1$ and $\tilde{\tau}_2$ with truncated Gaussian r.v. κ_1 and κ_2:

$$\begin{aligned} \tilde{\tau}_1 &= \tau_1 + \kappa_1 \\ \tilde{\tau}_2 &= \tau_2 + \kappa_2 \end{aligned} \quad (3)$$

Proposition 1

Having stochastic time delays $\tilde{\tau}_1$ and $\tilde{\tau}_2$ is equivalent to adding noises into the input vector $u_n(t; \tau_1, \tau_2)$ with fixed time delays τ_1 and τ_2, i.e.,

$$u_n(t; \tilde{\tau}_1, \tilde{\tau}_2) = u_n(t; \tau_1, \tau_2) + C(t) \quad (4)$$

where $C(t)$ represents the noises caused by stochastic time delay.

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Augmented State

Define a augmented state variable $\tilde{s}(t) = [x_n(t), v_n(t), \sigma_n(t)]^\intercal$.
Augmented state-space model

$$\begin{aligned}
\dot{\tilde{s}}_n(t) &= \mathcal{T}(s_n(t-\tilde{\tau}_1), u_n(t;\tilde{\tau}_1,\tilde{\tau}_2)) + \theta(t) \\
z_n(t_k) &= \mathcal{M}(\tilde{s}_n(t_k)) + \eta(t_k),\ k \in \{0 \cup \mathbb{Z}^+\}. \\
&\Downarrow \\
\dot{\tilde{s}}_n(t) &= \mathcal{T}(s_n(t-\tau_1), u_n(t;\tau_1,\tau_2)) + \tilde{\theta}(t) \\
z_n(t_k) &= \mathcal{M}(\tilde{s}_n(t_k)) + \eta(t_k),\ k \in \{0 \cup \mathbb{Z}^+\}
\end{aligned} \tag{5}$$

Filtering and Detection

- Augmented State extended Kalman filter (ASEKF)
  - Nonlinear motion model
  - Smooth sensor reading
- χ^2-detector
  - Constructs χ^2 test statistics to classify anomalies
  - A "circular" boundary over zero point
- One Class Support Vector Machine (OCSVM)
  - Learn normal data behavior
  - Trained with normalized innovation
    $\bar{\nu}(k) = S^{-\frac{1}{2}}(k) \cdot \nu(k)$

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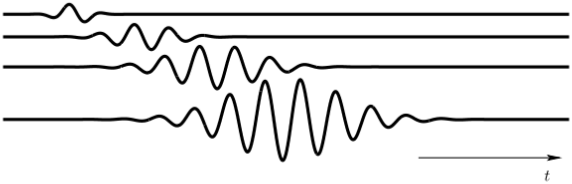
String Stability Analysis

Head-to-tail Stability

A platoon is called head-to-tail string stable if any perturbations that cause the first vehicle in the platoon (i.e., the platoon head) to deviate from its equilibrium state can be attenuated at the very last vehicle (i.e. the platoon tail).

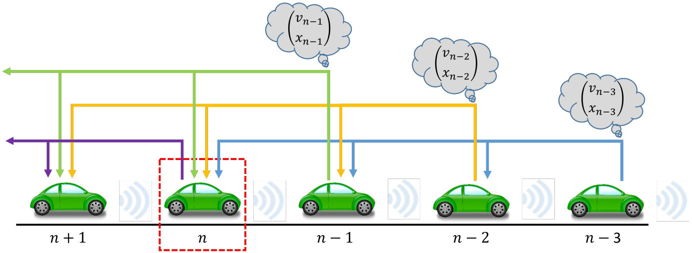


Source: Wilson and Ward, 2011

State Space Model

- Assume M-predecessor following (MPF) information flow topology
- Homogeneous vehicle in the platoon
- Introduce perturbations

$$\begin{aligned}\tilde{x}_n(t) &= x_n^*(t) - x_n(t) \\ \tilde{v}_n(t) &= v_n^*(t) - v_n(t)\end{aligned} \tag{6}$$



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State Space Model Cont

- Define the state as $\tilde{s}_n(t) = \begin{bmatrix} \tilde{x}_n(t) \\ \tilde{v}_n(t) \end{bmatrix} \Bigg($
- The dynamic model after linearization:

$$\dot{\tilde{v}}_n(t) = f_n^v \tilde{v}_n(t-\tau_1) + f_n^g \Big(\alpha_{n1} w_{n1}(t-\tau_1)\tilde{g}_n(t-\tau_1) + \sum_{j=2}^{M} \alpha_{nj} w_{nj}(t-\tau_2)\tilde{g}_{n-j+1}(t-\tau_2) \Big)$$
$$+ f_n^{\Delta v} \Big(\beta_{n1} w_{n1}(t-\tau_1)\Delta\tilde{v}_n(t-\tau_1) + \sum_{j=2}^{M} \beta_{nj} w_{nj}(t-\tau_2)\Delta\tilde{v}_{n-j+1}(t-\tau_2) \Big) \quad (7)$$

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State Space Model Cont

- Obtain the state space model:

$$
\begin{aligned}
\dot{\tilde{s}}_n(t) &= \begin{bmatrix} \dot{\tilde{x}}_n(t) \\ \dot{\tilde{v}}_n(t) \end{bmatrix} \\
&= \begin{bmatrix} 0 & 1 \\ 0 & 0 \end{bmatrix} \cdot \begin{bmatrix} \tilde{x}_n(t) \\ \tilde{v}_n(t) \end{bmatrix} + \begin{bmatrix} 0 & 0 \\ -\alpha_1 f_n^g & f_n^v + \beta_1 f_n^{\Delta v} \end{bmatrix} \cdot \begin{bmatrix} \tilde{x}_n(t-\tau_1) \\ \tilde{v}_n(t-\tau_1) \end{bmatrix} \\
&\quad + \sum_{j=1}^{M-1} \begin{bmatrix} 0 & 0 \\ (\alpha_j - \alpha_{j+1}) f_n^g & (\beta_{j+1} - \beta_j) f_n^{\Delta v} \end{bmatrix} \cdot \begin{bmatrix} \tilde{x}_{n-j}(t-\tau_2) \\ \tilde{v}_{n-j}(t-\tau_2) \end{bmatrix} \\
&\quad + \begin{bmatrix} 0 & 0 \\ \alpha_M f_n^g & -\beta_M f_n^{\Delta v} \end{bmatrix} \cdot \begin{bmatrix} \tilde{x}_{n-M}(t-\tau_2) \\ \tilde{v}_{n-M}(t-\tau_2) \end{bmatrix} \\
y_n(t) &= \begin{bmatrix} 0 & 1 \end{bmatrix} \cdot \begin{bmatrix} \tilde{x}_n(t) \\ \tilde{v}_n(t) \end{bmatrix}
\end{aligned}
\tag{8}
$$

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Transfer Function

- Conduct Laplace transformation on the state space model (8):

$$Y_n(s) = \begin{bmatrix} 0 & 1 \end{bmatrix} \cdot \left(sI - \begin{bmatrix} 0 & 1 \\ 0 & 0 \end{bmatrix} - A_n^{\tau_1} \cdot e^{-s\tau_1} \right)^{-1} \cdot \left[\left(\sum_{j=1}^{M} B_{n-j}^{\tau_2} Y_{n-j}(s) \right) \cdot e^{-s\tau_2} \begin{bmatrix} \frac{1}{s} \\ 1 \end{bmatrix} \right]$$
$$= \sum_{j=1}^{M} T_{n-j}(s) Y_{n-j}(s) \tag{9}$$

where

$$A_n^{\tau_1} = \begin{bmatrix} 0 & 0 \\ -\alpha_1 f_n^g & f_n^v + \beta_1 f_n^{\Delta v} \end{bmatrix}$$
$$B_{n-j}^{\tau_2} = \begin{bmatrix} 0 & 0 \\ (\alpha_j - \alpha_{j+1}) f_n^g & (\beta_{j+1} - \beta_j) f_n^{\Delta v} \end{bmatrix}, \; 1 \leq j \leq M-1 \tag{10}$$
$$B_{n-M}^{\tau_2} = \begin{bmatrix} 0 & 0 \\ \alpha_M f_n^g & -\beta_M f_n^{\Delta v} \end{bmatrix}$$

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Transfer Function Cont (1)

- Consider the head-to-tail transfer function

$$Y_n(s) = G_{n,0}(s)Y_0(s) \tag{11}$$

- Substitute equation (11) into equation (9), one can get:

$$G_{n,0}(s) = \sum_{m=1}^{M} \Big(T_{n-m}(s)G_{n-m,0}(s) \tag{12}$$

Transfer Function Cont (2)

- Recast into matrix form

$$\mathcal{G}_n(s) = \hat{P}_n(s) \cdot \mathcal{G}_{n-1}(s) \tag{13}$$

where

$$\mathcal{G}_n(s) = \begin{bmatrix} G_{n,0}(s) & G_{n-1,0}(s) & \dots & G_{n-M,0}(s) \end{bmatrix}^\intercal$$

$$\hat{P}_n(s) = \begin{bmatrix} T_{n-1}(s) & T_{n-2}(s) & \dots & T_{n-M}(s) & 0 \\ 1 & 0 & \dots & 0 & 0 \\ 0 & 1 & \dots & 0 & 0 \\ \vdots & \vdots & \ddots & \vdots & \vdots \\ 0 & 0 & \dots & 1 & 0 \end{bmatrix}$$

- The string stability is checked by

$$\sup_{\forall \omega > 0} |\lambda_k(\hat{P}_n(i\omega))| < 1, \quad k = 1, 2, ..., M \tag{14}$$

where $\lambda_k(\hat{P}_n(i\omega))$ is the k-th eigenvalue of the transfer matrix $\hat{P}_n(i\omega)$ with frequency ω.

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Impact of Detection Sensitivity on Stability

- Attacker conducts false injection/jamming attack on the entire platoon
- Detection recall/sensitivity p
- Once detected, recover signal from other sources
- Platoon model becomes a stochastic model instead of a deterministic one.

$$\dot{v}_n(t) = \eta_t f\left(v_n(t-\tau_1), \bar{g}_n(t;\tau_1,\tau_2), \bar{d}_n(t;\tau_1,\tau_2)\right) + (1-\eta_t)\cdot f\left(v_n(t-\tilde{\tau}_1)+\tilde{A}, \bar{g}_n(t;\tilde{\tau}_1,\tilde{\tau}_2)+\tilde{B}, \bar{d}_n(t;\tilde{\tau}_1,\tilde{\tau}_2)+\tilde{C}\right)\Bigg(\tag{15}$$

where $\mathbb{P}(\eta_t = 1) = \tilde{p} = p^N$ and $\mathbb{P}(\eta_t = 0) = 1 - \tilde{p}$.

- Transfer matrix is stochastic $\hat{P}_n(s;\Lambda)$

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Pseudo String Stability under Model Uncertainty

Pseudo String Stability

Consider a vehicle string with semi-infinite length in equilibrium state. Impose a transient perturbation on the head vehicle. The vehicle string is pseudo string stable if the perturbation eventually vanishes when reaching the tail vehicle in the string.

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Pseudo String Stability under Model Uncertainty Cont

- Original transfer matrix of the normal model

$$\hat{P}_n(s) = \begin{bmatrix} T_{n-1}(s) & T_{n-2}(s) & \dots & T_{n-M}(s) & 0 \\ 1 & 0 & \dots & 0 & 0 \\ 0 & 1 & \dots & 0 & 0 \\ \vdots & \vdots & \ddots & \vdots & \vdots \\ 0 & 0 & \dots & 1 & 0 \end{bmatrix} \tag{16}$$

- Denote the transfer matrix of the compromised model as

$$\hat{P}_n(s;\Lambda) = \begin{bmatrix} T_{n-1}(s;\Lambda) & T_{n-2}(s;\Lambda) & \dots & T_{n-M}(s;\Lambda) & 0 \\ 1 & 0 & \dots & 0 & 0 \\ 0 & 1 & \dots & 0 & 0 \\ \vdots & \vdots & \ddots & \vdots & \vdots \\ 0 & 0 & \dots & 1 & 0 \end{bmatrix} \tag{17}$$

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Pseudo String Stability under Model Uncertainty Cont

- Given a detection sensitivity $\tilde{p}$,

$$\begin{aligned}\bar{\hat{P}}_n(s;\Lambda) &:= \mathbb{E}_{\tilde{p}}\left[\hat{P}_n(s;\Lambda,\tilde{p})\right] \\ &= \tilde{p}\cdot\hat{P}_n(s) + (1-\tilde{p})\cdot\hat{P}_n(s;\Lambda) \\ &= \begin{bmatrix} \bar{T}_{n-1}(s;\Lambda) & \bar{T}_{n-2}(s;\Lambda) & \dots & \bar{T}_{n-M}(s;\Lambda) & 0 \\ 1 & 0 & \dots & 0 & 0 \\ 0 & 1 & \dots & 0 & 0 \\ \vdots & \vdots & \ddots & \vdots & \vdots \\ 0 & 0 & \dots & 1 & 0 \end{bmatrix}\end{aligned} \tag{18}$$

  where $\bar{T}_i(s;\Lambda) = \tilde{p}\cdot T_i(s) + (1-\tilde{p})\cdot T_i(s;\Lambda)$.

- Given a stochastic model $\mathcal{F}(\tilde{p},\hat{\xi})$, it is pseudo string stable if it satisfies

$$\underset{\forall\omega>0}{sup}\ \lambda_k(\bar{\hat{P}}_n(i\omega;\Lambda)) < 1, \quad k = 1,2,...,M$$

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Experimental Results

Detection Performance – Experiment Setup

- CIDM from (Wang et al., 2020a):

$$\dot{v}_n(t) = a^* \left(1 - \left(\frac{v_n(t)}{v_0}\right)^4 - \left(\frac{S^*(v_n(t), \bar{d}_n(t;\tau_1,\tau_2))}{\bar{g}_n(t;\tau_1,\tau_2)}\right) \right) \text{ with} \tag{19}$$

$$S^*(v_n(t), \bar{d}_n(t;\tau_1,\tau_2)) = s_0 + T \cdot v_n(t) + \frac{v_n(t) \cdot \bar{d}_n(t;\tau_1,\tau_2)}{2\sqrt{a^* b^*}}$$

  with 10 vehicles in the platoon.

- Five anomaly types (Wang et al., 2020b) – ‘short’, ‘noise’, ‘bias’, ‘gradual drift’, and ‘miss’ are injected to the 5-th vehicle in the platoon. The duration and magnitude of each type of anomaly are generated randomly.

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Detection Performance

Table 1: *Detection performance of three scenarios measuring on AUC scores of ROC curve and PR curve.*

Time Delay	Scen 1: $\tau_1 = \tau_2 = 0$ s		Scen 2: $\mathbb{E}[\tilde{\tau}_1] = \mathbb{E}[\tilde{\tau}_2] = 0.5$ s		Scen 3: $\mathbb{E}[\tilde{\tau}_1] = \mathbb{E}[\tilde{\tau}_2] = 1.5$ s	
Metric	ROC AUC	PR AUC	ROC AUC	PR AUC	ROC AUC	PR AUC
χ^2 EKF	0.968 $\pm$ 0.018	0.922 $\pm$ 0.054	0.946 $\pm$ 0.018	0.895 $\pm$ 0.054	0.866 $\pm$ 0.016	0.820 $\pm$ 0.049
χ^2 ASEKF	0.968 $\pm$ 0.021	0.920 $\pm$ 0.056	0.953 $\pm$ 0.024	0.902 $\pm$ 0.060	0.938 $\pm$ 0.030	0.866 $\pm$ 0.068
OCSVM EKF	**0.977 $\pm$ 0.011**	**0.959 $\pm$ 0.020**	**0.974 $\pm$ 0.010**	**0.956 $\pm$ 0.019**	**0.964 $\pm$ 0.012**	**0.933 $\pm$ 0.019**
OCSVM ASEKF	0.970 $\pm$ 0.017	0.933 $\pm$ 0.019	0.966 $\pm$ 0.014	0.936 $\pm$ 0.026	0.959 $\pm$ 0.014	0.931 $\pm$ 0.024

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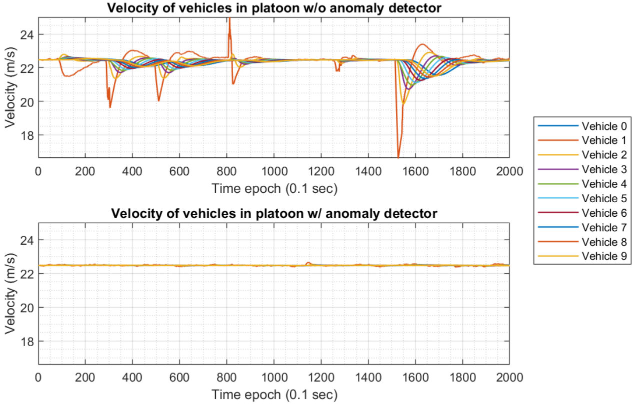
Detection Performance under Multiple Vehicle Attacks

Figure 1: *Vehicle velocity in platoon. Top: without detection and recovery. Bottom: with detection and recovery.*



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Detection Performance under Multiple Vehicle Attacks Cont

Figure 2: *Spacing error over time under cyber attacks. Top: without anomaly detection and recovery. Bottom: with anomaly detection and recovery.*

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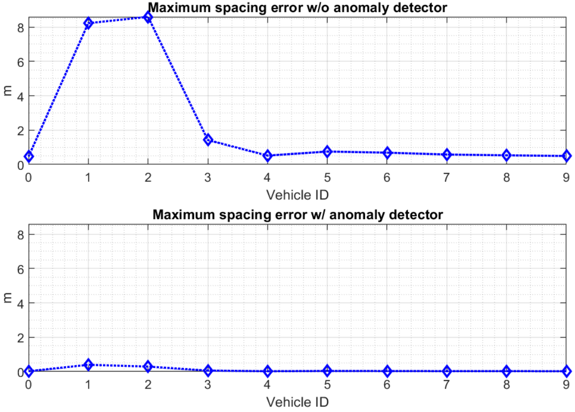
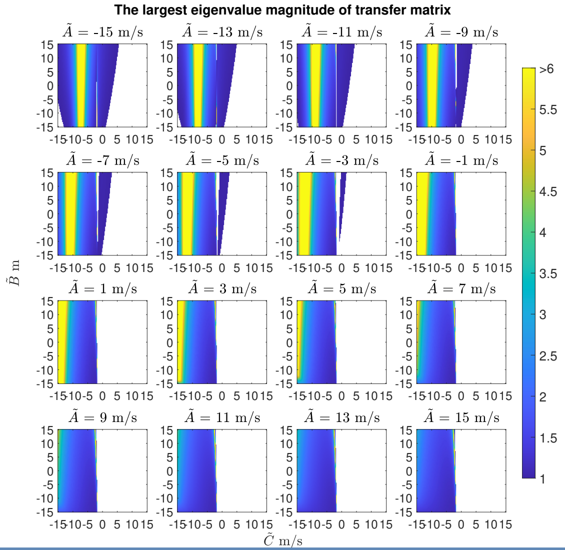
Detection Performance under Multiple Vehicle Attacks Cont

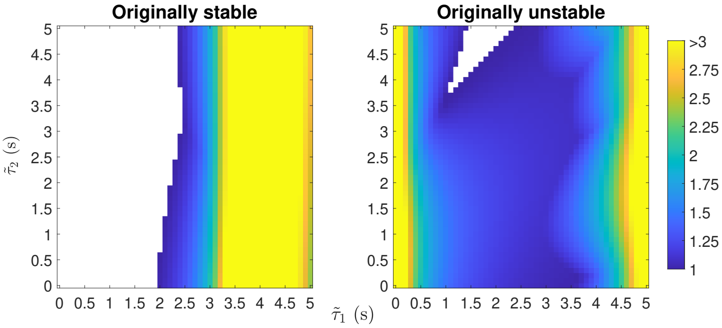
Figure 3: *Maximum absolute spacing error under cyber attacks. Top: without anomaly detection. Bottom: with anomaly detection and recovery.*



Sensitivity Analysis on the Attack Parameters

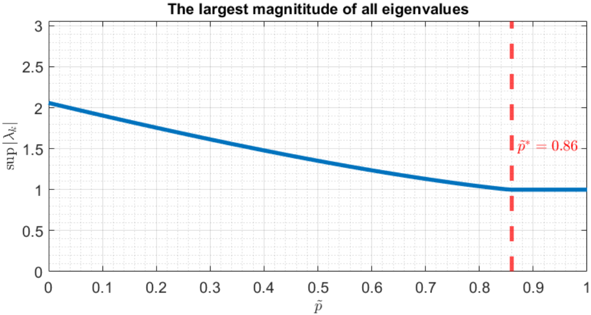


Sensitivity Analysis on the Attack Parameters Cont

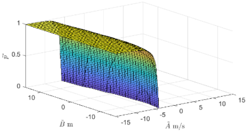


Pseudo String Stability Analysis

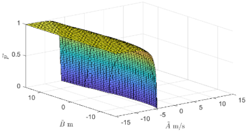
- It is critical to find a minimum required detection sensitivity/recall such that any detector with a higher detection sensitivity can make the platoon maintain pseudo string stability.



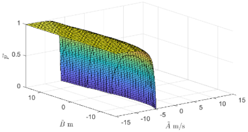
Pseudo String Stability Analysis Cont (1)



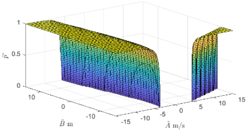
(a) $\tilde{\tau}_1 = 0$ s, $\tilde{\tau}_2 = 0$ s



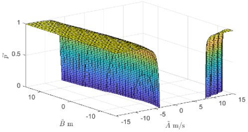
(b) $\tilde{\tau}_1 = 0$ s, $\tilde{\tau}_2 = 1$ s



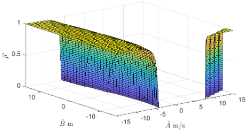
(c) $\tilde{\tau}_1 = 0$ s, $\tilde{\tau}_2 = 2$ s



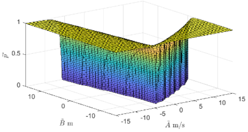
(d) $\tilde{\tau}_1 = 1$ s, $\tilde{\tau}_2 = 0$ s



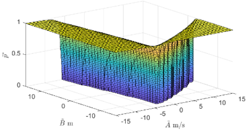
(e) $\tilde{\tau}_1 = 1$ s, $\tilde{\tau}_2 = 1$ s



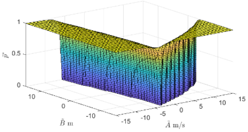
(f) $\tilde{\tau}_1 = 1$ s, $\tilde{\tau}_2 = 2$ s



(g) $\tilde{\tau}_1 = 2$ s, $\tilde{\tau}_2 = 0$ s



(h) $\tilde{\tau}_1 = 2$ s, $\tilde{\tau}_2 = 1$ s



(i) $\tilde{\tau}_1 = 2$ s, $\tilde{\tau}_2 = 2$ s

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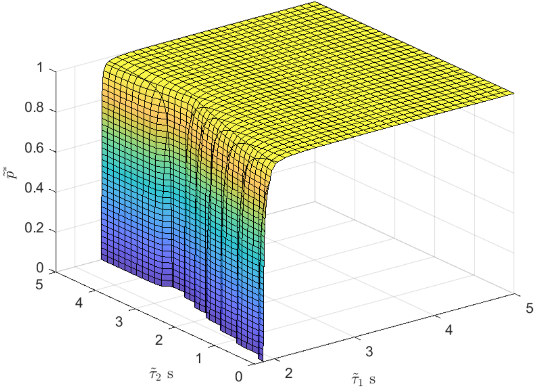
Pseudo String Stability Analysis Cont (2)



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Concluding Remark

- Solutions
  - State-space model of vehicle motion and sensor measurement with stochastic time delay
  - ASEKF with anomaly detector (χ^2 detector and OCSVM)
  - Pseudo string stability analysis under cyberattack
- Results
  - OCSVM outperforms χ^2 detector
  - Closed-form expression between detection sensitivity and pseudo string stability

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Open Question

Does the critical detection sensitivity $\tilde{p}^*$ always exist? Is it always unique?

- When $M = 3$, the eigenvalues of $\bar{\hat{P}}_n(i\omega; \Lambda)$ are the roots of the cubic equation

$$\lambda^3 - \bar{T}_{n-1}(s;\Lambda)\lambda^2 - \bar{T}_{n-2}(s;\Lambda)\lambda - \bar{T}_{n-3}(s;\Lambda) = 0 \tag{20}$$

  where $\bar{T}_i(s;\Lambda) = \tilde{p} \cdot T_i(s) + (1-\tilde{p}) \cdot T_i(s;\Lambda)$.

How about $M \geq 4$?

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Thank you

Q&A