Secure Platooning of Autonomous Vehicles
Under Attacked GPS Data

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Abstract—In this paper, we study how to secure the platooning of autonomous vehicles when an unknown vehicle is under attack and bounded system uncertainties exist. For the attacked vehicle, its position and speed measurements from GPS can be manipulated arbitrarily by a malicious attacker. First, to find out which vehicle is under attack, two detectors are proposed by using the relative measurements (by camera or radar) and the local innovation obtained through measurements from neighboring vehicles. Then, based on the results of the detectors, we design a local state observer for each vehicle by applying a saturation method to the measurement innovation. Moreover, based on the neighbor state estimates provided by the observer, a distributed controller is proposed to achieve the consensus in vehicle speed and keep fixed desired distance between two neighboring vehicles. The estimation error by the observer and the platooning error by the controller are shown to be asymptotically upper bounded under certain conditions. The effectiveness of the proposed methods is also evaluated in numerical simulations.

I. INTRODUCTION

The potential to enable fast and reconfigurable mechanisms for increasingly prevalent Automated Driving Systems (ADS), cooperative intelligent transportation systems (C-ITS), and vehicle platooning, as well as compelling mobility and safety benefits, underscores the critical need to develop more reliable and secure distributed-system designs in intelligent transport. In vehicle platooning and cooperative adaptive cruise controls (CACC), estimating the current vehicle states, which are shared via communication between vehicles, is essential for stability and traction control, as well as motion planning [1]–[4]. Vehicle (longitudinal and lateral) speeds can be measured by a GPS, but their reliability due to loss of reception and the poor accuracy of available commercial GPSs, specifically in measuring sideslip (and lateral speed), necessitates developing a reliable state estimators in connected ADS that share measurements and local estimates over Dedicated Short-Range Communications (DSRC) or 5G NR access via 3GPP PC5 or IEEE 802.11p technologies.

Vehicle platooning has enhanced in recent years in terms of reliability through vehicle-to-vehicle (V2V) connectivity, distributed state estimation, and learning-aided controls [5]–[7]. However, the existing secure platooning solutions in C-ITS are prohibitively inefficient in dealing with malicious attacks on GPS measurements. Such attacks could be through transmission of the received GPS data (in data acquisition modules) to ADS’ control systems or the GPS receiver. Thus, reliable state estimation, resilient to attacks and robust to system uncertainties, plays key roles in ensuring the safety of intelligent transport by improving the reliability of vehicle local active safety systems and enhancing the performance in cooperative tasks such as CACC [8], [9]. Real-time methods are proposed in [10], [11] to diagnose jamming Denial-of-Service (DoS) attacks in IEEE 802.11p vehicular networks and its false alarm probabilities are estimated. A data-driven fault detection approach and a decision support system are proposed in [12] to diagnose attacks and track fault data injection attacks in CACC (in real time).

To mitigate the DoS attack in CACC, a set of linear Luenberger observers is designed in [13] by using LMI over delayed measurements to develop a resilient control strategy. An adaptive control strategy is designed in [14] to deal with time-invariant sensor and actuator attacks in a vehicular network, with wireless V2V communication, while guaranteeing uniform boundedness of the closed-loop system. A decentralized proportional-derivative controller augmented by a triggering mechanism for getting preceding vehicles’ new measurements is designed in [15] to maintain string stability in a vehicular platoon. A trust-based service recommendation scheme is proposed in [16] to avoid selecting badly behaved head vehicles for ballot-stuffing and onoff attacks in vehicular ad hoc networks. In [17], [18] cooperative control protocols and state observers are provided for enhancing resilience to attacks and detecting faults in vehicular platoons.

To this end, by using available secure radar and stereo camera, which are available in autonomous vehicles, ADS, and advanced driver-assistance systems, and the potentially attacked GPS data in an unknown vehicle, this paper studies how to design a secure algorithm such that a group of autonomous vehicles achieve practical platooning. The main contributions of this paper are summarized in the following.

1) To find out which vehicle is under attack, we propose two detectors by using the relative measurements and the local innovation obtained through the absolute and relative measurements of three neighboring vehicles, respectively. Then, based on the results of the detectors, we design a local state observer for each vehicle by applying a saturation method to the measurement innovation.

2) Based on the neighbor state estimates provided by the observer, we design a distributed controller to achieve
consensus in vehicle speed and keeping fixed desired distance between two neighboring vehicles. It is also shown that the estimation error (by the observer) and the platooning error are asymptotically upper bounded under certain conditions.

The remainder of the paper is organized as follows: Section II is on the problem formulation. Section III provides the secure platooning algorithm, whose performance is studied in Section IV. After numerical simulations in Section V, the paper is concluded in Section VI. The main proofs are given in Appendix.

A. Notations

The superscript “T” represents the transpose. \( \mathbb{R}^{n \times m} \) is the set of real matrices with \( n \) rows and \( m \) columns. \( \mathbb{R}^{n} \) is the \( n \)-dimensional Euclidean space. \( I_{n} \) stands for the \( n \)-dimensional square identity matrix. \( \text{diag} \{ \cdot \} \) represents the diagonalization operator. \( A \otimes B \) is the Kronecker product of \( A \) and \( B \). \( \|x\| \) is the 2-norm of a vector \( x \). \( \| A \| \) is the induced 2-norm, i.e., \( \| A \| = \sup_{x \neq 0} \frac{\|Ax\|}{\|x\|} \). \( \lambda_{\min}(A) \) and \( \lambda_{\max}(A) \) are the minimal and maximal eigenvalues of a real-valued symmetric matrix \( A \), respectively. \( I_{e} \in C \) stands for the indicator function, which equals 1 if \( i \in C \), and 0 otherwise.

II. PROBLEM FORMULATION

A. System model

Considering \( N \geq 3 \) vehicles, without loss of generality, we assume that the order of these vehicles from the leader to the tail is 1, 2, \ldots, \( N \). The leader vehicle, i.e., vehicle 1, satisfies the following dynamics:

\[
    x_1(t+1) = Ax_1(t) + n_1(t),
\]

and vehicle \( i, i = 2,3, \ldots, N \), satisfies

\[
    x_i(t+1) = Ax_i(t) + [0, Tu_i(t)]^T + n_i(t),
\]

where \( x_j(t) = [s_j(t), v_j(t)]^T \in \mathbb{R}^2 \) is the state of vehicle \( j \) consisting of position \( s_j(t) \) and velocity \( v_j(t) \), \( n_j(t) \in \mathbb{R}^2 \) is the process noise, \( u_i(t) \in \mathbb{R} \) is the control input. \( A = \begin{pmatrix} 0 & T \end{pmatrix} \), and \( T \) the sampling time, \( j = 1,2,\ldots,N \).

Vehicle \( j \in \{1,2,\ldots,N\} \), obtains its position and velocity measurements from GPS:

\[
    y_{j,j}(t) = x_j(t) + a_j(t) + d_{j,j}(t),
\]

where \( y_{j,j}(t) \in \mathbb{R}^2 \) and \( d_{j,j}(t) \in \mathbb{R}^2 \) are the measurement and measurement noise of vehicle \( j \). \( a_j(t) \in \mathbb{R}^2 \) is the attack signal injected by a malicious attacker.

Moreover, by employing the vehicle sensors (e.g., radar and camera), vehicle \( i \in \{2,3,\ldots,N\} \) is able to measure the relative state between itself and its front vehicle (i.e., vehicle 1 - 1):

\[
    y_{i-1,i}(t) = x_i(t) - x_{i-1}(t) + d_{i-1,i}(t),
\]

where \( y_{i-1,i}(t) \in \mathbb{R}^2 \) and \( d_{i-1,i}(t) \in \mathbb{R}^2 \) are the measurement and measurement noise. Note that in this paper we assume the relative state measurements are attack-free.

Fig. 1. Platoon model and communication topology of seven vehicles: Each vehicle is able to measure the relative state between itself and its front vehicle by radar or camera (i.e., \( y_{j,i}, j \in \mathcal{N}_i \)). For two vehicles connected by wireless communications (e.g., WIFI), they can exchange their absolute and relative measurements (i.e., \( y_{j,i} \) and \( y_{j,j}, j \in \mathcal{N}_i \)), and the predicted estimates of own states (i.e., \( \hat{x}_i(t) \)).

Assumption 1: On the noise processes in (1) - (4) and the initial estimate \( \hat{x}_j(0) \), for \( j \in \{1,\ldots,N\} \), and \( i \in \{2,\ldots,N\} \), it holds that

\[
    \|\hat{x}_j(0) - x_j(0)\| \leq q, \\
    \|n_j(t)\| \leq \epsilon, \\
    \max\|d_{j,j}(t)\|, \|d_{j-1,j}(t)\| \leq \mu,
\]

where \( q, \epsilon, \mu \) are positive real-valued scalars known to each vehicle.

B. Attack model

Denote \( \mathcal{V} = \{1,2,\ldots,N\} \), \( \mathcal{A} \) the label set of the attacked vehicle, and \( \mathcal{A}^c = \mathcal{V} - \mathcal{A} \) the label set of attack-free vehicles.

Assumption 2: There is an unknown vehicle \( j \in \mathcal{V} \) under attack, i.e., \( \mathcal{A} = \{j\} \), such that the attack signal \( a_j(t) \) in (3) satisfies

\[
    a_j(t) \in \mathbb{R}^2, i = j, \\
    a_j(t) = 0, i \neq j.
\]

From Assumption 2 the GPS measurements of the attacked vehicle \( j \) can be manipulated arbitrarily. There is tradeoff on the use of the measurements. On one hand, if the measurements are fully trusted by conventional observers, once the vehicle is under attack, the estimation performance would be seriously degraded by the injected attack signals. On the other hand, if little confidence is given to the measurements, the estimation performance would be also degraded, since little information is utilized. Therefore, it is worth studying how to employ the potentially attacked measurements and how to design detectors to find out the attacked vehicle.

C. Communication of vehicles

We denote \( \mathcal{N}_i \) the neighbor set of vehicle \( i \), where \( \mathcal{N}_i = \{i-1, i\} \) if \( i \in \{2,\ldots,N-1\} \), \( \mathcal{N}_1 = \{2,3\} \), and \( \mathcal{N}_N = \{N-2, N-1\} \). The communication topology of the vehicles is illustrated in Fig. 1 with \( N = 7 \), where each vehicle \( i, i \in \{1,2,\ldots,N\}, \) can receive the measurements of its neighboring vehicle \( j, j \in \mathcal{N}_i \), including both absolute and relative measurements in (3) and (4). Note that for the leader and tail vehicles, i.e., vehicle 1 and vehicle \( N \), to ensure the redundancy of measurement information against the possible attacks on them, we require that vehicle 1 can obtain the measurements from vehicles 2 and 3, and that vehicle \( N \) can obtain the measurements from vehicles \( N-1 \) and \( N-2 \).
**Problem:** We aim to design the control input \( u_i(t) \) for vehicles \( i, 2 \leq i \leq N \), such that their speeds are close to the speed of the leader vehicle 1 and two neighboring vehicles keep a certain distance in position, i.e.,

\[
\begin{align*}
\limsup_{t \to \infty} |v_i(t) - v_1(t)| & \leq \gamma_1, \\
\limsup_{t \to \infty} |s_i(t) - s_{i-1}(t) - \Delta_{i,i-1}| & \leq \gamma_2,
\end{align*}
\]

against the attack signal \( \{a_i(t), i \in A\} \) injected by some malicious attacker, where \( \gamma_1 \) and \( \gamma_2 \) are nonnegative real-valued scalars, related to the system noise.

**III. Co-design of observer, detector, and controller**

In this section, for each vehicle \( i, i \in \{2, \ldots, N\} \), we will first design a local state observer to estimate its velocity and position, then develop two local attack detectors to find out whether it is under attack, and finally provide a distributed controller by employing the estimates from neighboring vehicles to achieve the vehicle platooning in [5].

### A. Observer design

By (27)-(29), the measurement equation for vehicle \( i, i \in \{1, \ldots, N\} \), can be written in the following:

\[
z_i(t) = Cx_i(t) + a_i(t) + d_i(t)
\]

where

\[
\begin{align*}
z_i(t) &= \begin{bmatrix} y_{11}(t) \ t_y(12(t)) \ t_y(13(t)) \end{bmatrix}^T, \\
a_i(t) &= \begin{bmatrix} a_{11}^T(t) \ a_{12}^T(t) \ a_{13}^T(t) \end{bmatrix}^T, \\
d_i(t) &= \begin{bmatrix} d_{11}(t) \ d_{12}(t) \ d_{13}(t) \end{bmatrix}^T, \\
z_i(t) &= \begin{bmatrix} y_{i1}(t) \ t_y(i1(t)) \ t_y(i1(t)) \end{bmatrix}^T, 2 \leq i \leq N - 1, \\
a_i(t) &= \begin{bmatrix} a_{i1}^T(t) \ a_{i2}^T(t) \ a_{i3}^T(t) \end{bmatrix}^T, \\
d_i(t) &= \begin{bmatrix} d_{i1}(t) \ d_{i2}(t) \ d_{i3}(t) \end{bmatrix}^T, \\
v_N(t) &= \begin{bmatrix} y_{N1}(N-2(t)) \ t_y(N1(N-1)(t)) \ t_y(N1(N)(t)) \end{bmatrix}^T, \\
a_N(t) &= \begin{bmatrix} a_{N1}(t) \ a_{N2}(t) \ a_{N3}(t) \end{bmatrix}^T, \\
d_N(t) &= \begin{bmatrix} d_{N1}(N-2(t)) \ d_{N1}(N-1(t)) \ d_{N1}(N(t)) \end{bmatrix}^T, \\
C &= \begin{bmatrix} I_{2 \times 2} \\
I_{2 \times 2} \\
I_{2 \times 2} \\
\end{bmatrix}
\]

with the notations in (7) are given in Appendix [A]. Note that \( y_{i1(j)} \), \( j = i - 1, i + 1 \) stands for the absolute measurement of vehicle \( i \) calculated with the relative measurement between vehicles \( i \) and \( j \).

Since the leader vehicle is control-free, i.e., \( u_1(t) = 0 \), from (1), (2), and (6), we have the reformulated state equation and measurement equation of vehicle \( i, i \in \{1, \ldots, N\} \), in the following

\[
x_i(t + 1) = Ax_i(t) + [0, T u_i(t)]^T + n_i(t) \\
z_i(t) = Cx_i(t) + a_i(t) + d_i(t).
\]

We aim to design an observer for vehicle \( i \) with two steps, namely, time update and measurement update. In the time update, for vehicle \( i \), we let

\[
\hat{x}_i(t) = A\hat{x}_i(t - 1) + [0, T u_i(t - 1)]^T,
\]

where \( \hat{x}_i(t) \) is the estimate of \( x_i(t) \). Then we denote the measurement innovation of vehicle \( i \) at time \( t \) by \( \eta_i(t) \), where

\[
\eta_i(t) = z_i(t) - C\hat{x}_i(t).
\]

To number the labels of vehicles in the measurement update equation, we let

\[
\eta_i(t) := \begin{bmatrix} n_{i1}(t) & n_{i2}(t) & n_{i3}(t) \end{bmatrix}^T
\]

\[
K_i(t) = \begin{bmatrix} k_{i1}(t) & k_{i2}(t) & k_{i3}(t) \end{bmatrix},
\]

where \( j_1, j_2, j_3 \in \mathbb{N} \cup \{t\} \). For example, from equation (6), if \( i = 1, j_1 = 1, j_2 = 2, j_3 = 3 \), and if \( i = 2, j_1 = 2, j_2 = 2, j_3 = 3 \). Otherwise, \( j_1 = i - 1, j_2 = i, j_3 = i + 1 \). Then we design a saturation-like scheme to utilize the measurement \( \eta_i(t) \) as follows.

For each \( m = \{1, 2, 3\} \), and for each \( r = \{1, 2\} \),

\[
k^r_{i,m}(t) = \begin{cases} 1, & \text{if } |\eta^r_{i,m}(t)| \leq \beta, \\
\beta |\eta^r_{i,m}(t)|, & \text{otherwise},
\end{cases}
\]

where \( \beta \geq 0 \) is a saturation parameter to be designed in the following. From equations (11) and (12), the update equation is given:

\[
\hat{x}_i(t) = \hat{x}_i(t) + \frac{1}{2} C^T K_i(t)\eta_i(t), i \in \{1, \ldots, N\}.
\]

### B. Detector design

Although the saturation based estimation method provided in the previous subsection can be employed directly to estimate vehicle state (position and speed), under potentially attacked GPS measurements, an attack detection protocol is provided in the following to identify the vehicle under attack.

When the attacked vehicle is identified, we provide an attack-free estimation approach by isolating the measurements of the attacked vehicle to improve the estimation performance.

The idea of the first detector is that for two attack-free vehicles, the norm of the difference between the relative measurements and the absolute measurements is upper bounded by a scalar related to the noise bound. Otherwise, one of the two vehicles is under attack.

**Lemma 1:** For each attack-free vehicle \( i \geq 2 \) and \( i - 1, \) e.g., \( i \in \{2, \ldots, N\} \cap A^c \), if Assumption [1] holds,

\[
||f_{i,i-1}(t)|| \leq 3\mu,
\]

where \( f_{i,i-1}(t) = y_{i-1,i}(t) + y_{i-1,i}(t) - y_{i,i}(t) \).

**Proof:** By equation (5), for \( i \in \{2, \ldots, N\} \cap A^c,

\[
y_{i,i}(t) = x_{i}(t) + d_{i,i}(t),
\]

\[
y_{i-1,i-1}(t) = x_{i-1}(t) + d_{i-1,i-1}(t).
\]

From equation (4),

\[
y_{i-1,i}(t) = x_{i}(t) - x_{i-1}(t) + d_{i-1,i-1}(t).
\]


Then substituting (14) into (15) yields
\[ f_{i,i-1}(t) = d_{i-1,i}(t) + d_{i-1,i-1}(t) + d_{i,i}(t). \] (16)

Taking the norm of both sides of (16) leads to the conclusion.

Let \( \Gamma_i(t) \) be the detected set of the attacked vehicle by vehicle \( i \) at time \( t \), which contains the label of the attacked vehicle. Let \( \Theta_i(t) \) be the detected-with-doubt vehicle set at time \( t \) by vehicle \( i \), which contains the labels of two vehicles and one of them is the attacked vehicle. At the initial time, we assume \( \Gamma_i(0) = \emptyset \) and \( \Theta_i(0) = \emptyset \), \( i \in \{1, \ldots, N\} \).

The sets \( \Gamma_i(t) \) and \( \Theta_i(t) \) are shared between neighboring vehicles. From Lemma 1, we propose the following detector to identify the attacked vehicle.

**Detector 1:** For vehicle \( i \in \{2, \ldots, N - 1\} \), test the inequalities in [1] and [2]: for vehicle \( i = 1 \), test the inequality in [3], for vehicle \( i = N \), test the inequality in [4].

1. \( \|f_{i,i-1}(t)\| > 3\mu \)
2. \( \|f_{i+1,i}(t)\| > 3\mu \)

then

- if there is a time \( t \) such that [1] holds, either vehicle \( i \) or \( i - 1 \) is under attack, and we let \( \Theta_i(t) = \{i-1, i\} \);
- if there is a time \( t \) such that [2] holds, either vehicle \( i \) or \( i + 1 \) is under attack, and we let \( \Theta_i(t) = \{i, i+1\} \);
- if there are two times under which [1] and [2] hold respectively, then vehicle \( i \) is claimed to be under attack and we let \( \Gamma_i(t) = \{i\} \).

**Proposition 1:** Under Assumptions [1][2] for Detector 1, all the three claims hold.

**Proof:** From Assumption [1] and Lemma 1 the first and second claims hold. Furthermore, under Assumption [2] the third claim holds.

The idea of the second detector is that for an attack-free vehicle, its measurement innovation is upper bounded by a sequence related to the estimation error. Otherwise, this vehicle is under attack. Define the sequence \( \{\rho(t)\} \) in the following

\[ \rho(t + 1) = (1 - k(t + 1)) \|A\| \rho(t) + Q, \] (17)

where \( \rho(0) = q \), and

\[ k(t + 1) = \min\{1, \frac{\beta}{\|A\| \rho(t) + \epsilon + \mu}\}, \]

\[ Q = \frac{3}{2} (\epsilon + \mu) + \frac{\sqrt{2}}{2} \beta. \] (18)

**Lemma 2:** Under Assumption [1] for each vehicle \( i \in \{1, \ldots, N\} \),

- \( \|\hat{x}_i(t) - x_i(t)\| \leq \rho(t) \);
- if vehicle \( i \) is attack-free, i.e., \( i \in A^c \), then for \( t \geq 1 \),

\[ \|y_i(t) - A\hat{x}_i(t - 1)\| \leq \|A\| \rho(t - 1) + \epsilon + \mu. \]

where \( \rho(t) \) is in (17).

**Proof:** See Appendix.

Based on Lemma 2, we provide the following detector.

**Detector 2:** We claim vehicle \( i \) is under attack and let \( \Gamma_i(t) = \{i\} \), if

\[ \|y_i(t) - A\hat{x}_i(t - 1)\| > \|A\| \rho(t - 1) + \epsilon + \mu, \]

where \( \rho(t - 1) \) is in (17).

If the attacked vehicle, e.g., vehicle \( s \in \Gamma_i \), is found out by Detector 2 or two potentially attacked vehicles are found out by Detector 1, e.g., vehicles \( l, l + 1 \in \Theta_i(t) \), to remove the influence of the measurements of the vehicles or vehicle \( l, l + 1 \) to the estimation performance, the observer gains \( K_i(t) \), of all the vehicles are supposed to be adjusted as follows. Recall the form of \( K_i(t) \) in (14):

\[ K_i(t) = \text{diag}(k_{i,i-1}^{[1]}(t), k_{i,i+1}^{[1]}(t), k_{i,j}^{[2]}(t), k_{i,j}^{[2]}(t)), \] (19)

Then we provide the design of the elements \( k_{i,j}^{[r]}(t) \), \( r = 1, 2 \), and \( m = 1, 2, 3 \) in the following.

If \( \Gamma_i(t) = \{s\} \), let

\[ k_{i,s}^{[1]}(t) = 0, k_{i,s}^{[2]}(t) = 0, \forall s \in \bar{N}_i, \]

\[ k_{i,i}^{[1]}(t) = 1, k_{i,i}^{[2]}(t) = 1, l \neq s, l \in \bar{N}_i, \] (20)

where \( \bar{N}_i = N_i \cup \{i\} \).

If \( \Gamma_i(t) = \emptyset \) but \( \Theta_i(t) \neq \emptyset \), let

\[ k_{i,i}^{[1]}(t) = 0, k_{i,s}^{[2]}(t) = 0, \forall s \in N_i \cap \Theta_i(t), \]

\[ k_{i,i}^{[1]}(t) = 1, k_{i,i}^{[2]}(t) = 1, l \neq s, l \in \bar{N}_i. \] (21)

In other cases, the design of \( K_i(t) \) remains the same as equation (12), i.e., for each \( m = \{1, 2, 3\} \), and for each \( r = \{1, 2\} \),

\[ k_{i,j,m}^{[r]}(t) = \begin{cases} 1, & \text{if } |y_i^{[r]}(t)| \leq \beta, \\ \frac{1}{|y_i^{[r]}(t)|}, & \text{otherwise} \end{cases} \] (22)

Based on the designed \( K_i(t) \), all the measurements of the attack-free vehicles will not be saturated and the measurements of the possible attacked vehicles (e.g., the detected vehicles) will no longer be employed.

**C. Controller design**

Next, we aim to design the control input based on the neighbor estimates and the desired relative position distance between two neighboring vehicles. Denote \( N_i \) the set of vehicle(s) nearest to vehicle \( i \), i.e.,

\[ N_i = \begin{cases} \{i - 1, i + 1\}, & \text{if } i \in \{2, 3, \ldots, N - 1\} \\ \{2\}, & \text{if } i = 1 \\ \{N - 1\}, & \text{if } i = N. \end{cases} \] (23)

Note that \( N_i \subset N_i, \forall i \in \{1, 2, \ldots, N\} \).

Assume \( \hat{s}_i(t) \) and \( \hat{v}_i(t) \) are the estimates of \( s_i(t) \) and \( v_i(t) \), respectively. Let \( t_i^* \) be the start time for the control input. For \( 0 \leq t < t_i^* \), we let \( u_i(t) = 0 \). Regarding the acceleration \( u_i(t) \) in (9), by employing the predicted estimates \( \hat{x}_i(t) = \hat{x}_i(t) \).
with the following acceleration input, for $t \geq t^*_i \geq 0$,

$$u_i(t) = \sum_{j \in \mathcal{N}_i} (g_s(s_j(t) - \hat{s}_i(t) + \Delta_{i,j}) \quad \text{(24)}$$

$$+ g_v(\bar{v}_j(t) - \hat{v}_i(t))), 2 \leq i \leq N,$$ 

where $g_s$ and $g_v$ are positive scalars to be determined. Note that if the initial estimates are very accurate, we can choose $t^*_i = 0$. Otherwise, setting a larger $t^*_i$ can lead to better estimates but need more time to achieve the platooning of vehicles.

Based on the observer, the two detectors and the distributed controller, for the system (8), we propose the secure platooning algorithm for vehicle $i$ in Algorithm 1.

Algorithm 1 Secure Autonomous Vehicle Platooning:

1: Initial setting: $(\bar{x}_i(0), \beta, g_s, g_v)$

2: Communications between neighboring vehicles: Vehicle $i$ sends out its measurements $y_{i-1,i}(t)$, $y_{i,i}(t)$, the sets $\Theta_i(t-1)$ and $\Gamma_i(t-1)$, and the estimate $\hat{x}_i(t)$ to its neighboring vehicle $j \in \mathcal{N}_i$. Let $\Gamma_i(t) = \bigcup_{j \in \mathcal{N}_i} \Gamma_j(t-1) \cup \Gamma_i(t-1)$ and $\Theta_i(t) = \bigcup_{j \in \mathcal{N}_i} \Theta_j(t-1) \cup \Theta_i(t-1)$. Then vehicle $i$ runs Detector 2.

3: Measurement update: Vehicle $i$, $i \in \{1, \ldots, N\}$, uses the measurement $z_i(t)$ in (6) to update its own state estimate

$$\eta_i(t) = z_i(t) - C\bar{x}_i(t).$$

Run Detector 2 to update $\Theta_i(t)$ and $\Gamma_i(t)$. The estimate is updated in the following,

$$\hat{x}_i(t) = \bar{x}_i(t) + \frac{1}{2} C^T K_i(t) \eta_i(t),$$

where $K_i(t)$ is designed by (19)-(22).

4: Control input: Vehicle $i$ uses its own estimate $\hat{x}_i(t)$ and the predicted estimates $\bar{x}_j(t)$, $j \in \mathcal{N}_i$, from its neighbors to design the input $u_i(t)$: $u_i(t) = 0$, if $0 \leq t \leq t^*_i$; for $t \geq t^*_i$,

$$u_i(t) = \sum_{j \in \mathcal{N}_i} (g_s(s_j(t) - \hat{s}_i(t) + \Delta_{i,j}) \quad \text{(25)}$$

$$+ g_v(\bar{v}_j(t) - \hat{v}_i(t))), 2 \leq i \leq N.$$

5: Time update:

$$\bar{x}_i(t+1) = A\hat{x}_i(t) + [0, Tu_i(t)]^T.$$

IV. ALGORITHM PERFORMANCE

In this section, we would like to study the performance of Algorithm 1. First, we study the condition to ensure the asymptotically bounded estimation error. Then, we provide the design for the control parameters such that the platooning error of vehicles are asymptotically bounded.

In the following theorem, we study the boundedness of the estimation error for Algorithm 1.

Theorem 1: Consider the system (8) satisfying Assumptions [4] and Algorithm 1. If the following condition holds

$$(1 - k^*) \|A\| q + \frac{3}{2} (\epsilon + \mu) + \frac{\sqrt{2}}{2} \beta < q, \quad \text{(26)}$$

then the estimation error is uniformly upper bounded, i.e.,

$$\limsup_{t \to \infty} \|\hat{x}_i(t) - x_i(t)\| \leq \alpha, i \in \{1, \ldots, N\},$$

where $k^* = \min\{1, \frac{\beta}{\|A\|q + \epsilon + \mu}\}$, and $\alpha$ is given in (31).

Proof: See Appendix.

We note that if $\epsilon, \mu, T$ are sufficiently small, (26) is satisfied by choosing $\beta = p$. The boundedness of the vehicle platooning error is studied in the following theorem.

Theorem 2: Under the same conditions as Theorem 1, if

$$\lambda_{\max}(L_y) < \frac{4g_s}{g_v^2}, T < \frac{g_v}{g_s} \quad \text{(27)}$$

then for $i = 2, \ldots, N$, there exist constants $\gamma_1$ and $\gamma_2$ such that

$$\limsup_{t \to \infty} |v_i(t) - v_1(t)| \leq \gamma_1,$$

$$\limsup_{t \to \infty} |s_i(t) - s_{i-1}(t) + \Delta_{i,i-1}| \leq \gamma_2.$$

Proof: See Appendix.

V. NUMERICAL SIMULATIONS

In this section, we study numerical simulations to show the effectiveness of the proposed algorithm in the vehicle platooning under attacked GPS data.

Suppose there are five vehicles, in which the GPS measurement data of vehicle 3 is compromised by a malicious attacker. The attacker will insert the signal $a_3(t) = 2\bar{y}_{3,3}(t)$, where $\bar{y}_{3,3}(t)$ is the attack-free GPS measurement of vehicle 3. We suppose the time interval $t = [0, 1000]$ with sampling step $T = 1$ second. Both the process noise $v_i(t)$ and measurement noise $d_{i,j}(t), j \in \mathcal{N}_i \cup \{i\}, i = 1, \ldots, 5$, follow the uniform distribution between $[-0.1, 0.1]$. The bounds in Assumption 1 are assumed to be $\mu = 0.1, \epsilon = 0.1, q = 100.5$. The initial state is $x_1(0) = (100, 10)^T, x_2(0) = (60, 8)^T, x_3(0) = (40, 6)^T, x_4(0) = (20, 4)^T, x_5(0) = (0, 2)^T$, whose estimates are all $0^5 \times 1$. The required distance between vehicles $i$ and $j \in \mathcal{N}_i$ is $\Delta_{i,j} = 20$.

We conduct a Monte Carlo experiment with 100 runs. Define the average estimation error in position and velocity by $\eta_{i,v}(t)$ and $\eta_{i,v}(t)$, respectively, where

$$\eta_{i,v}(t) = \frac{1}{100} \sum_{j=1}^{100} |d_{i,v}(t)|,$$

and $d_{i,v}(t)$ and $d_{i,v}(t)$ are the state estimation errors of vehicle $i$ in position and velocity, respectively, at time $t$ in the $j$th run.
Moreover, we define the relative position and velocity between vehicle \( i \in \{2, 3, 4, 5\} \) and the leader vehicle 1 by \( \zeta_{i,s}(t) \) and \( \zeta_{i,v}(t) \), respectively, where

\[
\zeta_{i,s}(t) = \frac{1}{100} \sum_{j=1}^{100} (s_i^j(t) - s_1^j(t)),
\]

\[
\zeta_{i,v}(t) = \frac{1}{100} \sum_{j=1}^{100} (v_i^j(t) - v_1^j(t)),
\]

and \( s_i^j(t) \) and \( v_i^j(t) \) are the position and velocity of vehicle \( i \), respectively, at time \( t \) in the \( j \)th run.

First, we use a conventional algorithm, which has the same controller as Algorithm 1 but all \( k_{i,j,m}^{[r]}(t) = 1, r = 1, 2, m = 1, 2, 3, i \in \{1, \ldots, 5\} \) in the observer. For the case that the GPS data of vehicle 3 is under attack, the simulation result is given in Fig. 2. It shows that both the estimation error and the platooning error show serious fluctuations. The average crash number\(^1\) of the vehicles is 179. For Algorithm 1, we choose \( q_s = 0.5 \), which satisfies the condition in (26). The control input starts at time \( t^* = 50 \). Also, we choose \( \beta = 1 \). The simulation results are provided in Fig. 3 and Fig. 4. The attacked vehicle 3 is successfully detected at \( t = 2 \). Fig. 3 shows that the estimation errors of all vehicles tend to zero. In Fig. 4 the relative positions of vehicles are ensured and all the velocities of the following vehicles tend to the velocity of the leader vehicle 1.

VI. CONCLUSION

This paper studied how to design a secure algorithm such that a group of autonomous vehicles achieve platooning under the case that the GPS data of one vehicle is under attack. We provided a distributed algorithm, which consists of a local state observer, two online attack detectors and a distributed controller. The conditions to ensure bounded state estimation error and vehicle platooning error were studied.

\(^1\)The crash number is the times where the order from the leader vehicle 1 to the tail vehicle \( N \) is different from 1, 2, \ldots, \( N \).

APPENDIX

A. Derivation of (6)

For vehicle \( i \in \{2, 3, \ldots, N - 1\} \), by (3) and (4), we have

\[
\begin{align*}
y_{i|i-1}(t) & = x_i(t) + a_{i-1}(t) + d_{i|i-1}(t) \\
y_{i|i+1}(t) & = x_i(t) + a_{i+1}(t) + d_{i|i+1}(t)
\end{align*}
\]

(27)

where

\[
\begin{align*}
y_{i|i-1}(t) & = y_{i-1,i}(t) + y_{i-1,i-1}(t) \\
y_{i|i+1}(t) & = y_{i+1,i}(t) - y_{i,i+1}(t) \\
d_{i|i-1}(t) & = d_{i-1,i}(t) + d_{i-1,i-1}(t) \\
d_{i|i+1}(t) & = d_{i+1,i}(t) - d_{i,i+1}(t).
\end{align*}
\]

For vehicle 1,

\[
\begin{align*}
y_{1|2}(t) & = x_1(t) + a_2(t) + d_{1|2}(t) \\
y_{1|3}(t) & = x_1(t) + a_3(t) + d_{1|3}(t)
\end{align*}
\]

(28)
where

\[
y_{12}(t) = y_{22}(t) - y_{12}(t) \\
y_{13}(t) = y_{33}(t) - y_{13}(t) - y_{23}(t) \\
d_{12}(t) = d_{22}(t) - d_{12}(t) \\
d_{13}(t) = d_{33}(t) - d_{12}(t) - d_{23}(t).
\]

For vehicle \( N \),

\[
y_{N,N-1}(t) = x_N(t) + a_{N-1}(t) + d_{N,N-1}(t) \\
y_{N,N-2}(t) = x_N(t) + a_{N-2}(t) + d_{N,N-2}(t)
\] (29)

where

\[
y_{N,N-1}(t) = y_{N-1,N}(t) + y_{N-1,N-1}(t) \\
y_{N,N-2}(t) = y_{N-1,N}(t) + y_{N-2,N-1}(t) + y_{N-2,N-2}(t) \\
d_{N,N-1}(t) = d_{N-1,N}(t) + d_{N-1,N-1}(t) \\
d_{N,N-2}(t) = d_{N-1,N}(t) + d_{N-2,N-1}(t) + d_{N-2,N-2}(t).
\]

From (27), (29), (6) is obtained.

**B. Proof of Lemma [2]**

Let \( e_i(t) = \hat{x}_i(t) - x_i(t), \ i \in \{1, \ldots, N\} \). We use an inductive method to prove the two conclusions. At the initial time, under Assumption [1], \( \|e_i(0)\| \leq q \). For an attack-free vehicle \( i \), by equations (1)–(3),

\[
\|y_{i,i}(t) - A\hat{x}_i(0)\| = \| - Ae_i(0) + n_i(1) + d_{i,i}(1)\| \leq \|A\| q + \epsilon + \mu.
\]

Assume at time \( t - 1 \),

\[
\|e_i(t-1)\| \leq \rho(t-1) \\
\|y_{i,i}(t) - A\hat{x}_i(t-1)\| \leq \|A\| \rho(t-1) + \epsilon + \mu.
\]

Denote

\[
\begin{align*}
\tilde{K}_{i,A'}(t) &= \text{diag} \left\{ k_{1,j_1}(t)_{j_1} \in A', k_{2,j_2}(t)_{j_2} \in A', k_{1,j_2}(t)_{j_2} \in A', k_{2,j_1}(t)_{j_1} \in A' \right\} \\
&\in \mathbb{R}^{6 \times 6},
\end{align*}
\]

As we see, \( \tilde{K}_{i,A'}(t) \) is diagonal and its diagonal elements are zero if the corresponding vehicles are under attack. Then we define the complementary of \( \tilde{K}_{i,A'}(t) \) with respect to \( \tilde{K}_i(t) \):

\[
\tilde{K}_{i,A}(t) = \tilde{K}_i(t) - \tilde{K}_{i,A'}(t).
\]

Let \( \tilde{K}_{i,j}(t) \) be the \( j \)-th diagonal element of \( \tilde{K}_i(t), j = 1, \ldots, 6 \), and \( d_{i,j}(t) \) be the \( j \)-th element of \( d_i(t) \). Denote

\[
\mathbf{K}_i(t) = \begin{pmatrix}
\sum_{j=1,3,5} \tilde{K}_{i,j}(t) & 0 \\
0 & \sum_{j=2,4,6} \tilde{K}_{i,j}(t)
\end{pmatrix} \in \mathbb{R}^{2 \times 2}
\]

\[
W_i(t) = \sum_{j=1,3,5} \begin{pmatrix}
\tilde{K}_{i,j}(t) & 0 \\
0 & \tilde{K}_{i,j+1}(t)
\end{pmatrix} \begin{pmatrix}
d_{i,j}(t) \\
d_{i,j+1}(t)
\end{pmatrix} \in \mathbb{R}^2.
\]

By Algorithm [1] we have

\[
e_i(t) = Ae_i(t - 1) + \frac{1}{2} C^T \tilde{K}_i(t)(z_i(t) - C\tilde{x}_i(t))
\]

\[
= (I_2 - \frac{1}{2} \tilde{K}_i(t))Ae_i(t - 1) + \frac{1}{2} \tilde{K}_i(t)n_i + \frac{1}{2} W_i(t)
+ \frac{1}{2} C^T \tilde{K}_{i,A}(t)(z_i(t) - C\tilde{x}_i(t)).
\]

Taking the norm operation of \( e_i(t) \) yields

\[
\|e_i(t)\| \leq \|(I_2 - \frac{1}{2} \tilde{K}_i(t))A\| e_i(t - 1) + |A|_{\epsilon,\mu} \|e_i(t-1)\| + |A|_{\sqrt{\frac{1}{2}} \beta} q + |A|_Q \|e_i(t-1)\| + Q
\]

\[
\leq (1 - k(t)) \|A\| \rho(t - 1) + Q
\]

\[
= \rho(t).
\] (30)

For an attack-free vehicle \( i \), by equations (1)–(3),

\[
\|y_{i,i}(t + 1) - A\hat{x}_i(t)\| = \| - Ae_i(t) + n_i(t + 1) + d_{i,i}(t + 1)\| \leq \|A\| \rho(t) + \epsilon + \mu.
\]

**C. Proof of Theorem [7]**

From Lemma [2], \( \|\hat{x}_i(t) - x_i(t)\| \leq \rho(t) \). The conclusion of this theorem holds if \( \limsup_{t \to \infty} \rho(t) \leq \alpha \), which will be proved in the following.

Let \( k^* = \min \{ 1, \frac{\beta}{\|A\| + \mu} \} \). Next, we prove \( \rho(t) < q \) for \( t \geq 1 \). From (18) and \( \rho(0) = q \), \( k(1) \geq k^* \). By (17), \( \rho(1) = (1 - k(1)) \|A\| \rho(0) + Q \leq (1 - k^*) \|A\| q + Q < q \). Suppose at time \( t, \rho(t) < q \). At time \( t + 1 \), from (18) and \( k(t + 1) < k^* \). By (17), \( \rho(t + 1) < (1 - k^*) \|A\| q + Q < q \). Thus, \( \rho(t) < q \) for \( t \geq 1 \).

Note that \( 0 < \|A(1 - k^*)\| < 1 \), if (25) is satisfied and \( k^* \neq 1 \). As a result, for \( i \in \{1, \ldots, N\} \), we have

\[
\limsup_{t \to \infty} \rho(t)
\]

\[
\leq \alpha := Q \left( \frac{1}{1 - \|A(1 - k^*)\|} \right)^{k^* - 1},
\]

\[
\text{where} \ Q = \frac{3}{2} (\epsilon + \mu) + \frac{\sqrt{2}}{2} \beta.
\] (31)

**D. Proof of Theorem [2]**

Suppose \( x_i^*(t) = [s_i^*(t), v_i^*(t)]^T \) is the desired state of vehicle \( i \). Denote the tracking error of vehicle \( i, 2 \leq i \leq N \), by \( \hat{x}_i(t) = [\hat{s}_i(t), \hat{v}_i(t)]^T \) which satisfies the following equation

\[
\hat{x}_i(t + 1) = A\hat{x}_i(t) + [0, T\tilde{u}_i(t)]^T + \delta_i(t)
\]

\[
\delta_i(t) = [0, T\tilde{u}_i(t)]^T + n_i(t)
\] (32) (33)

where

\[
\tilde{u}_i(t) = \sum_{j \in N_i} \left( g_v(\tilde{s}_j(t) - s_i(t))
+ g_v(\tilde{v}_j(t) - v_i(t)) \right), 2 \leq i \leq N, 1 \leq j \leq N,
\]

\[
\hat{u}_i(t) = \sum_{j \in N_i} \left( g_v(\tilde{s}_j(t) - s_i(t)) - (\hat{s}_i(t) - s_i(t))
+ g_v((\tilde{v}_j(t) - v_i(t)) - (\hat{v}_i(t) - v_i(t)))
\]. 
(34)
Let \( \tilde{X}(t) = [\tilde{x}_1(t)^T, \tilde{x}_2(t)^T, \ldots, \tilde{x}_N(t)^T] \) and \( \delta(t) = [\delta_1(t)^T, \delta_2(t)^T, \ldots, \delta_N(t)^T] \), then we have

\[
\tilde{X}(t + 1) = P \tilde{X}(t) + \delta(t),
\]

where \( P = I_{N-1} \otimes A - \mathcal{L}_g \otimes F, F = \begin{pmatrix} 0 & 0 \\ Tg_s & Tg_v \end{pmatrix} \) and \( \mathcal{L}_g \) is the ground Laplacian matrix with respect to the nodes \( \{2, 3, \ldots, N\} \) obtained by removing the first row and first column of the Laplacian matrix \( \mathcal{L} \).

By Theorem 1, \( \sup_{t \geq 0} \|\delta(t)\| < \infty \). Based on the BIBO stability principle, the stability of \( \tilde{X}(t) \) in (35) depends on \( P \). According to [19], the spectrum of \( \tilde{X}(t) \) in (35) is Schur stable. By Lemma 1, \( \sup_{t \geq 0} \|G(t)\| \leq \alpha_1 \), then we rewrite (38) in the following

\[
\limsup_{t \to \infty} \|x(t)\|^2 \leq \frac{\beta \alpha_1^2}{\lambda_{\min}(P)(1 - \lambda)};
\]

2) if \( \sup_{t \geq 0} \|G(t)\| \leq \alpha_2 \), then

\[
\limsup_{t \to \infty} \|x(t)\|^2 \leq \frac{\beta \alpha_2^2}{\lambda_{\min}(P)(1 - \lambda)}.
\]

**Proof:** First, it can be easily verified that \( P = \sum_{t=0}^{\infty}(F^T)^tF^t \) is the solution of \( F^TPF = -I_n \) with \( \lambda_{\min}(P) \geq 1 \). Let \( V(x(t)) = x(t)^TPx(t) \). Then we consider

\[
V(x(t + 1)) = V(x(t)) - G(t)^TPG(t) + 2x(t)^T F^T PG(t) - x(t)^T x(t)
\]

\[
= \|P\| \|G(t)\|^2 - \frac{1}{2} \|x(t)^T x(t) + 2G(t)^TPF^T PG(t)
\]

\[
\leq \beta \|G(t)\|^2 - \frac{1}{2\lambda_{\max}(P)} V(x(t)),
\]

where \( \beta = \|P\| \|G(t)\| \). By (40), we have

\[
V(x(t + 1)) \leq \lambda V(x(t)) + \beta \|G(t)\|^2.
\]

By applying (40) for \( t \) times, we have

\[
V(x(t)) \leq \lambda^t V(x(0)) + \beta \sum_{l=0}^{t-1} \lambda^{t-l-1} \|G(l)\|^2.
\]

The equation (38) is straightforward to be obtained by (41).

The conclusion in 1) is obtained by (38) and \( \lambda \in (0, 1) \). Next, we prove 2). To prove 2), we just need to prove that for any \( t \geq T_0 \), \( \|x(t)\|^2 \leq \frac{\beta \alpha_2^2}{\lambda_{\min}(P)(1 - \lambda)} + \epsilon_0 \). Due to \( \limsup_{t \to \infty} \|G(t)\| \leq \alpha_2 \), \( \forall \epsilon_1 > 0 \), there is a constant \( T_1 > 0 \), such that for any \( t \geq T_1 \), \( \|G(t)\| \leq \alpha_2 + \epsilon_1 \). Then we rewrite (38) in the following

\[
\|x(t)\|^2 \leq \lambda^{T_1} \lambda_{\max}(P) \|x(0)\|^2
\]

\[
+ \frac{\beta}{\lambda_{\max}(P)} \sum_{l=0}^{T_1-1} \lambda^{t-l-1} \|G(l)\|^2 + \frac{\beta}{\lambda_{\min}(P)} \sum_{l=T_1}^{t-1} \lambda^{t-l-1} \|G(l)\|^2.
\]

We analyze the three terms on the right-hand side of (42), respectively. First, due to \( \lambda \in (0, 1) \), there is a time \( T_2 > 0 \), such that \( t \geq T_2 \),

\[
\lambda^{T_1} \lambda_{\max}(P) \|x(0)\|^2 \leq \frac{\epsilon_0}{3}.
\]
Second, due to $\sup_{t \geq 0} \|G(t)\|^2 < \infty$, there is a time $T_3 > 0$, such that $t \geq T_3$,
\[ \frac{\beta}{\lambda_{\min}(P)} \sum_{t=0}^{T_3-1} \lambda^{t-1} \|G(t)\|^2 < \frac{\epsilon_0}{3}. \]  
(44)

Finally, recall that $\forall \epsilon_1 > 0$, $\|G(t)\| \leq \alpha_2 + \epsilon_1$ for any $t \geq T_1 + 1$. By taking $\epsilon_1 < \frac{\epsilon_0 \lambda_{\min}(P) (1 - \lambda)}{3 \lambda}$, we have
\[ \frac{\beta}{\lambda_{\min}(P)} \sum_{t=T_1}^{t-1} \lambda^{t-1} \|G(t)\|^2 \leq \frac{\beta \alpha_2}{\lambda_{\min}(P) (1 - \lambda)} + \frac{\beta \epsilon_1}{\lambda_{\min}(P) (1 - \lambda)} \leq \frac{\beta \alpha_2}{\lambda_{\min}(P) (1 - \lambda)} + \frac{\epsilon_0}{3}. \]  
(45)

Let $T_0 = \max\{T_1 + 1, T_2, T_3\}$. Then given $\forall \epsilon_0 > 0$, for any $t \geq T_0$, by (42)–(45), $\|x(t)\|^2 \leq \frac{\beta \alpha_2}{\lambda_{\min}(P) (1 - \lambda)} + \epsilon_0$. $\blacksquare$

References

[1] V. Milanès, S. E. Shladover, J. Spring, C. Nowakowski, H. Kawazoe, and M. Nakamura, “Cooperative adaptive cruise control in real traffic situations,” *IEEE Transactions on Intelligent Transportation Systems*, vol. 15, no. 1, pp. 296–305, 2014.

[2] K.-Y. Liang, J. Mårtensson, and K. H. Johansson, “Heavy-duty vehicle platoon formation for fuel efficiency,” *IEEE Transactions on Intelligent Transportation Systems*, vol. 17, no. 4, pp. 1051–1061, 2016.

[3] E. Siampis, E. Velenis, S. Garrioulo, and S. Longo, “A real-time nonlinear model predictive control strategy for stabilization of an electric vehicle at the limits of handling,” *IEEE Transactions on Control Systems Technology*, no. 99, pp. 1–13, 2017.

[4] M. Jalali, E. Hashemi, A. Khajepour, S.-K. Chen, and B. Litkouhi, “Integrated model predictive control and velocity estimation of electric vehicles,” *Mechatronics*, vol. 46, pp. 84–100, 2017.

[5] L. Cui, J. Hu, B. B. Park, and P. Bujanovic, “Development of a simulation platform for safety impact analysis considering vehicle dynamics, sensor errors, and communication latencies: Assessing cooperative adaptive cruise control under cyber attack,” *Transportation Research Part C: Emerging Technologies*, vol. 97, pp. 1–22, 2018.

[6] S. Ucar, S. C. Ergen, and O. Özkasap, “IEEE 802.11 p and visible light hybrid communication based secure autonomous platoon,” *IEEE Transactions on Vehicular Technology*, vol. 67, no. 9, pp. 8667–8681, 2018.

[7] X. Jin, W. M. Haddad, Z.-P. Jiang, A. Kanellopoulos, and K. G. Vamvoudakis, “An adaptive learning and control architecture for mitigating sensor and actuator attacks in connected autonomous vehicles,” *International Journal of Adaptive Control and Signal Processing*, vol. 33, no. 12, pp. 1788–1802, 2019.

[8] V. Turri, B. Besselink, and K. H. Johansson, “Cooperative look-ahead control for fuel-efficient and safe heavy-duty vehicle platooning,” *IEEE Transactions on Control Systems Technology*, vol. 25, no. 1, pp. 12–28, 2017.

[9] R. van der Heijden, T. Lukaseder, and F. Kargl, “Analyzing attacks on cooperative adaptive cruise control (CACC),” in *2017 IEEE Vehicular Networking Conference (VNC)*, pp. 45–52, IEEE, 2017.

[10] N. Lyamin, A. Vinel, M. Jonsson, and J. Loo, “Real-time detection of denial-of-service attacks in IEEE 802.11 p vehicular networks,” *IEEE Communications Letters*, vol. 18, no. 1, pp. 110–113, 2014.

[11] N. Lyamin, D. Kleyko, Q. Delouz, and A. Vinel, “Real-time jamming DoS detection in safety-critical V2V C-ITS using data mining,” *IEEE Communications Letters*, vol. 23, no. 3, pp. 442–445, 2019.

[12] A. Sargolzaei, C. D. Crane, A. Abbaspour, and S. Noei, “A machine learning approach for fault detection in vehicular cyber-physical systems,” in *2016 15th IEEE International Conference on Machine Learning and Applications (ICMLA)*, pp. 636–640, IEEE, 2016.