Distributed Platooning Control of Automated Vehicles Subject to Replay Attacks Based on Proportional Integral Observers

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***Abstract*—Secure platooning control plays an important role in enhancing the cooperative driving safety of automated vehicles subject to various security vulnerabilities. This paper focuses on the distributed secure control issue of automated vehicles affected by replay attacks. A proportional-integral-observer (PIO) with predetermined forgetting parameters is first constructed to acquire the dynamical information of vehicles. Then, a time-varying parameter and two positive scalars are employed to describe the temporal behavior of replay attacks. In light of such a scheme and the common properties of Laplace matrices, the closed-loop system with PIO-based controllers is transformed into a switched and time-delayed one. Furthermore, some sufficient conditions are derived to achieve the desired platooning performance by the view of the Lyapunov stability theory. The controller gains are analytically determined by resorting to the solution of certain matrix inequalities only dependent on maximum and minimum eigenvalues of communication topologies. Finally, a simulation example is provided to illustrate the effectiveness of the proposed control strategy.**

***Index Terms*—Automated vehicles, platooning control, proportional-integral-observers (PIOs), replay attacks, time-delays.**

I. Introduction

THE volume of traffic has been ever-increasing due mainly to the rapid development of urban transportation networks and highway systems. While providing the convenience of economic and social development, vehicles give rise to many considerable social problems, such as frequent traffic accidents, increasingly severe traffic congestion as well as increasingly energy cost [1]–[3]. Platooning control, as one effective means, has been developed to overcome such impressive issues by ensuring that vehicles run on roads as a team with the desired spacing and the same speed [4]–[7]. This kind of model not only guarantees the safety of vehicles but also increases transportation efficiency and hence has been attracted a great deal of attention from scholars. There is no doubt that platooning control is essentially formation control of multi-agent systems, for which the related approaches can be utilized to generate the desired platoon strategies. In the past few years, some interesting results have been reported in the literature, see [8] and the references therein. Compared with traditional multi-agent systems, the spacing strategy has to be prioritized in platooning control. Typical strategies include, but are not limited to, constant spacing [9], constant time headway [10], as well as variable time headway [11].

It should be mentioned that state-feedback control strategies can realize better platooning performance than output-feedback ones. However, in practical scenarios, the whole motion information on mobile vehicles cannot be easily measured directly. Therefore, it is necessary to propose an observer to estimate the motion information of vehicles in real time. Proportional-integral observers (PIOs) have been developed recently when the influence of accumulated estimate errors is a concern [12]. PIO is an extension of the Luenberger observer. Compared with the traditional Luenberger observer, the structure of PIOs involves an additional integral term, which makes it more robust and has better steady-state accuracy [13]–[15]. For instance, PIOs with gain variations have been developed in [14] in the framework of H_∞ filtering. The state-of-charge estimation based on RC battery models has been utilized in [16] to verify the superiority of proposed PIOs. The technique of unknown input proportional multiple-integral observer has been proposed in [17] to estimate the lumped disturbance of heterogeneous vehicle platoons subject to disturbances and modeling errors, and a novel PIO-based fault-tolerant tracking controller has been developed in [18] for automobile active suspensions encountered with actuator faults and parameter uncertainties. Recently, a PIO-based out-

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put tracking control scheme has been developed in [19] for time-delayed Markov jump systems, where equivalent input disturbance approaches have been utilized to improve the rejection performances. To the authors' knowledge, the research of PIO-based control is still in the primary stage, and the corresponding platooning control is still open, which is the motivation of our current research.

Automated vehicles will improve traffic safety and efficiency thanks to information can be exchanged wirelessly between vehicle-to-vehicle (V2V) or vehicle-to-infrastructure (V2I). However, under dense deployment scenarios, and with the introduction of connected automated vehicles that the requirements for communication bandwidth will also be higher, so V2V communication will also face challenges in terms of reliability and communication bandwidth. 5G is the latest generation of communication technology. The 5G technology ensures the network speed, reliability and time delay of communication. The application of 5G communication technology to the Internet of Vehicles can optimize the communication system of current autonomous driving technology and improve the data transmission rate. The 5G technology plays an important role in vehicle delay processing. It can improve the response speed of vehicles, take vehicle instructions in time, adjust vehicle driving information, and improve system safety. It is indispensable to guarantee the information exchange among vehicles in the task of platooning control via open V2V or V2I networks [20]–[22]. Due mainly to the network vulnerability, attacks could have the capability of invading communication networks and generate great impacts on the driving safety of vehicles and even cause fatal accidents. Generally speaking, common attacks can be divided into deception attacks [23]–[27], denial of service attacks [28]–[31] and replay attacks [32], [33]. Among several feasible attack mechanisms, replay attacks have been evaluated as being particularly dangerous. The replay attack is to replay the recorded historical data to the vehicle. Since the replayed data information is outdated, the system performance is degraded, and even the stability of the platooning is endangered. In the past few years, some preliminary results, focusing on secure platooning control, have been reported in the literature. For instance, an adaptive control scheme by means of neural networks has been proposed in [34] to achieve secure platooning control under deception attacks, and a resilient control protocol has been developed in [35] to realize the internal stability of vehicular physical systems under denial of service attacks. Furthermore, an adaptive control algorithm by considering the attack mitigation has been proposed in [36] to copy with a platoon formation undergoing cyber threats. In addition, a robust reset controller combined with a delay-robust speed synchronization controller have been designed in [37] to satisfy energy-to-peak performance of a connected vehicle subject to replay attacks, and a long short-term memory neural-network-based model has been proposed in [38] for detecting replay attack and amplitude-shift attack. It is worth pointing out that the influence of replay attacks has received less research attention in theoretical analysis, not to mention that the platooning control of automated vehicles is a concern.

Replay attacks have some typical characteristics a) an uncertain instant of their occurrence; b) an uncertain instant of historical data stored in caches; and c) the uncertain duration. Currently reported mathematical models cannot be easily embedded in the process of performance analysis, which results in enormous difficulties in security control. Furthermore, in the context of distributed platooning control, the following three fundamental challenges are identified: 1) how to provide a new approach to describe replay attacks; 2) how to establish a unified analysis framework under PIO-based controllers and replay attacks; and 3) how to develop a control scheme whose computation burden is insensitive to the number of vehicles. As such, this paper devotes itself to providing satisfactory answers about these three identified challenges, and the corresponding contributions are highlighted as follows: 1) A time-varying parameter and two positive scalars are introduced to deal with the temporal behavior of replay attacks, under which the discussed system is transformed into a switched and time-delayed one; 2) A sufficient condition dependent on the duration and the active ratio of replay attacks is received via the Lyapunov stability theory; 3) The desired gains of PIO-based controllers are designed by resorting to the solution of certain matrix inequalities only dependent on maximum and minimum eigenvalues of communication topologies.

The remaining sections of this paper are structured as follows. Section II formulates the PIO-based control problem for automated vehicles subject to replay attacks. Then, the stability analysis and the gain design of desired controllers are presented in Section III. In Section IV, an illustrative example is given to show the effectiveness of the proposed scheme. The conclusions are provided in Section V.

II. Problem Formulation and Preliminaries

This paper focuses on a homogeneous platoon of $N+1$ vehicles driving on a straight highway. Such a platoon includes a leading vehicle indexed by 0 and N following vehicles indexed from 1 to N. Vehicles share their status information through the V2V communication protocol, such as the absolute position, the speed as well as the acceleration. The objective of platooning control is to ensure that the entire platoon moves at the same speed and meanwhile maintains a constant distance between the front and rear vehicles.

Vehicles in a homogeneous platoon communicate with their neighbors via V2V channels. The V2V communication topology is described by a triple $G=(\mathcal{V},\mathcal{E},\mathcal{L})$ with the set $\mathcal{V}=\{1,2,\ldots,N\}$ for N following vehicles, the set $\mathcal{E}\subseteq\mathcal{V}\times\mathcal{V}$ for edges indicating the information exchange among following vehicles, and the associated adjacency matrix $\mathcal{L}=[l_{ij}]\in\mathbb{R}^{n\times n}$ representing the weights of V2V communication. Specifically $l_{ij}\neq 0$ if $(i,j)\in\mathcal{E}$, otherwise $l_{ij}=0$. Furthermore, the self-loop (i,i) is excluded in the graph, that is, $l_{ii}=0,\forall i\in\mathcal{V}$. The following vehicle j is called as a neighbor of the following vehicle i if its information can be accessed by the vehicle i and the corresponding neighboring set is denoted by $\mathcal{N}_i=\{j\in\mathcal{V}\mid l_{ij}\neq 0\}$. The Laplacian matrix induced by $\mathcal{L}$ is described as $H = [h_{ij}]_{N\times N}$ with $h_{ij} = -l_{ij}$ for $i \neq j$ and $h_{ij} = \sum_{j\in\mathcal{N}_i} l_{ij}$ for $i = j$. Considering the role of the leader, introduce a pinning matrix $Q = \text{diag}\{q_1, q_2, \ldots, q_N\}$ with $q_i = 1$ or $q_i = 0$. The following vehicle i can receive the command of the leader via V2V channels only when $q_i = 1$.

Assumption 1: The graph G associated with N following vehicles is undirected, and there exists at least one following vehicle to accept the command of the leader.

In light of the linearized third-order model adopted in literature [15], [39], [40], [41], the longitudinal dynamics of the i-th vehicle are described by

$$\pi \dddot{p}_i(t) + \ddot{p}_i(t) = u_i(t) \tag{1}$$

where $p_i(t) \in \mathbb{R}$, $\dot{p}_i(t) = v_i(t) \in \mathbb{R}$ and $\ddot{p}_i(t) = a_i(t) \in \mathbb{R}$ denote, respectively, the absolute position, velocity and acceleration; π represents the time delay in the powertrain systems; $u_i(t) \in \mathbb{R}$ is the desired control input imposed on the i-th vehicle.

For convenience, select the stacked state vector $x_i(t) = [p_i(t), v_i(t), a_i(t)]^T$ and then obtain the following dynamical model of the i-th vehicle:

$$\dot{x}_i(t) = Ax_i(t) + Bu_i(t) \tag{2}$$

where

$$A = \begin{bmatrix} 0 & 1 & 0 \\ 0 & 0 & 1 \\ 0 & 0 & -1/\pi \end{bmatrix}, \; B = \begin{bmatrix} 0 \\ 0 \\ 1/\pi \end{bmatrix}.$$

Furthermore, discretizing the above system with the sampling period h results in

$$x_i(k+1) = \mathcal{A}x_i(k) + \mathcal{B}u_i(k) \tag{3}$$

where

$$\mathcal{A} = \begin{bmatrix} 1 & h & 0 \\ 0 & 1 & h \\ 0 & 0 & e^{-\frac{h}{\pi}} \end{bmatrix}, \; \mathcal{B} = \begin{bmatrix} 0 \\ 0 \\ 1 - e^{-\frac{h}{\pi}} \end{bmatrix}.$$

Benefiting from the development of information technologies, vehicles are usually embedded with some onboard sensors capable of sensing partial motion information and could also transmit this information to related neighbors through V2V communication networks to realize safe driving. The measurement output $y_i(k) \in \mathbb{R}^{n_y}$ of sensors in the i-th vehicle is described by

$$y_i(k) = Cx_i(k) \tag{4}$$

where C is a known matrix of compatible dimensions.

Assumption 2: The phenomena of time delays or packet loss do not occurred for V2V communication.

It should be pointed out that whole motion information of a moving following vehicle could be unavailable in most practical scenarios. As such, the following onboard observer is constructed to estimate the specific information of positions, velocities, and accelerations

$$\begin{cases} \hat{x}_i(k+1) = \mathcal{A}\hat{x}_i(k) + \mathcal{B}u_i(k) \\ \qquad\qquad + \mathcal{L}_1(y_i(k) - C\hat{x}_i(k)) + \mathcal{L}_2\xi_i(k) \\ \xi_i(k+1) = \hbar\xi_i(k) + (y_i(k) - C\hat{x}_i(k)) \end{cases} \tag{5}$$

where $\hat{x}_i(k) = [\hat{p}_i(k), \hat{v}_i(k), \hat{a}_i(k)]^T$ is the estimate of vehicle state $x_i(k)$, and $\xi_i(k)$ refers to the accumulation (i.e., integral for continuous cases) of the estimated output errors. $\mathcal{L}_1$ and $\mathcal{L}_2$ are the observer gain matrices to be designed, and $\hbar$ is a predetermined forgetting parameter. In comparison with traditional ones, the constructed observer involves an accumulation loop and hence is essentially a PIO with a forgetting parameter. The introduced accumulation loop can effectively reduce the accumulated errors and improves the estimation performance. On the other hand, the matrix $\mathcal{B}$ is of full-column ranks and, therefore, can be decomposed to

$$E\mathcal{B}F = \begin{bmatrix} E_1 \\ E_2 \end{bmatrix} \mathcal{B}F = \begin{bmatrix} \Delta \\ 0 \end{bmatrix} \tag{6}$$

where $E = [E_1^T \;\; E_2^T]^T$ and F are two orthogonal matrices and Δ is the nonzero singular value of $\mathcal{B}$.

For the purpose of achieving the platooning control objective, the *ideal* PIO-based control signal $\tilde{u}_i(k)$ of the i-th following vehicle is designed as follows:

$$\tilde{u}_i(k) = \mathcal{K}\Big(\sum_{j\in\mathcal{N}_i} l_{ij}(\hat{x}_i(k) - \hat{x}_j(k) - \bar{d}_{ij}) \\ + q_i(\hat{x}_i(k) - x_0(k) - \bar{d}_{i0})\Big) \tag{7}$$

with the predetermined vector $\bar{d}_{ij} = [d_{ij}, 0, 0]^T$, where $\mathcal{K} = [k_p, k_v, k_a]$ is the desired controller gain to be designed. Here, $d_{ij} = d_{i0} - d_{j0}$ in the vector $\bar{d}_{ij}$ represents a prescribed constant spacing [9] between the vehicle i and the vehicle j. Such a spacing reflects the physical safety.

Due to the vulnerability of communication channels, the *actual* control signal could suffer from replay attacks. Under this kind of attack, attackers want to destroy the platoon performance via recording and covering the historically transmitted data. In this situation, the *actual* control law is modeled by

$$u_i(k) = \delta_k\tilde{u}_i(k) + (1 - \delta_k)\tilde{u}_i(p) \tag{8}$$

where p is a unknown positive scalar reflecting the recording instant of attackers, and δ_k is an indicator function used to describe whether the attacker launches a replay attack. Specifically, one has

$$\delta_k = \begin{cases} 0, & \text{replay attacks launched} \\ 1, & \text{otherwise.} \end{cases} \tag{9}$$

The replay attack should last a certain duration to realize the destroyed aim. In other words, the running duration can be divided into the attack-active duration and attack-silent one. As such, let us denote k_r as the attack launched instant, and $L_r = [k_r, k_r + \bar{\tau}_r)$ as the rth attack time interval, where $\bar{\tau}_r$ is the duration of the rth replay attack. As such, the time interval $[k_a, k_b)$ can be divided into two subintervals $\Omega(k_a, k_b)$ and $\Lambda(k_a, k_b)$ with $\Omega(k_a, k_b) \bigcup \Lambda(k_a, k_b) = [k_a, k_b)$ and $\Omega(k_a, k_b) \bigcap \Lambda(k_a, k_b) = \varnothing$ where $\Omega(k_a, k_b) = \cup_{r\in\mathbb{N}} L_r \cap [k_a, k_b)$ and $\Lambda(k_a, k_b) = [k_a, k_b) \setminus \Omega(k_a, k_b)$, under which the replay attacks are active and silent, respectively. Furthermore, the corresponding duration lengths are denoted as $|\Omega(k_a, k_b)|$ and $|\Lambda(k_a, k_b)|$.

To facilitate the performance analysis, define the estimate error and the platoon tracking errors as follows:

$$\begin{cases}\tilde{x}_i(k) = x_i(k) - \hat{x}_i(k)\\ e_i^p(k) = p_i(k) - p_0(k) - d_{i,0}\\ e_i^v(k) = v_i(k) - v_0(k)\\ e_i^a(k) = a_i(k) - a_0(k).\end{cases} \tag{10}$$

It is not difficult to obtain from (3) and (5) that

$$\begin{cases}\tilde{x}_{k+1} = (I_N \otimes \mathcal{A})\tilde{x}_k - (I_N \otimes \mathcal{L}_1 C)\tilde{x}_k\\ \qquad\qquad - (I_N \otimes \mathcal{L}_2)\xi_k\\ \xi_{k+1} = \hbar(I_N \otimes I_{n_y})\xi_k + (I_N \otimes C)\tilde{x}_k\end{cases} \tag{11}$$

with

$$\tilde{x}_k = [\ \tilde{x}_1^T(k) \quad \tilde{x}_2^T(k) \quad \cdots \quad \tilde{x}_N^T(k)\ ]^T$$
$$\xi_k = [\ \xi_1^T(k) \quad \xi_2^T(k) \quad \cdots \quad \xi_N^T(k)\ ]^T.$$

In what follows, let us introduce a time-varying parameter τ_k and two positive scalars m and s to deal with the temporal behavior of replay attacks. Specifically, one denotes $\tau_k = k - p$ satisfying $0 < s \le \tau_k \le m$, and then transforms the addressed platoon system into a class of time-varying delayed systems, where the scalar $\bar{\tau}_r = m - s + 1$ reflects the maximum duration of continuous replay attacks. Subsequently, denote $\tilde{e}_i(k) = [e_i^p(k), e_i^v(k), e_i^a(k)]^T$, and obtain the platoon tracking error dynamics from (3) and (8) as follows:

$$\tilde{e}_i(k+1) = \begin{cases}\mathcal{A}\tilde{e}_i(k) + \mathcal{BK}(\sum_{j\in\mathcal{N}_i} l_{ij}(\tilde{e}_i(k) - \tilde{e}_j(k)\\ \quad - \tilde{x}_i(k) + \tilde{x}_j(k)) + q_i(\tilde{e}_i(k) - \tilde{x}_i(k)))\\ \quad + \mathcal{A}\bar{d}_{i,0} - \bar{d}_{i,0},\ \ \delta_k = 1\\ \mathcal{A}\tilde{e}_i(k) + \mathcal{BK}(\sum_{j\in\mathcal{N}_i} l_{ij}(\tilde{e}_i(k-\tau_k)\\ \quad - \tilde{e}_j(k-\tau_k) - \tilde{x}_i(k-\tau_k) + \tilde{x}_j(k-\tau_k))\\ \quad + q_i(\tilde{e}_i(k-\tau_k) - \tilde{x}_i(k-\tau_k)))\\ \quad + \mathcal{A}\bar{d}_{i,0} - \bar{d}_{i,0},\ \ \delta_k = 0.\end{cases}$$

For the purpose of notational simplicity, denote

$$\tilde{e}_k = [\ \tilde{e}_1^T(k) \quad \tilde{e}_2^T(k) \quad \cdots \quad \tilde{e}_N^T(k)\ ]^T$$
$$\bar{d} = [\ \bar{d}_{1,0}^T \quad \bar{d}_{2,0}^T \quad \cdots \quad \bar{d}_{N,0}^T\ ]^T.$$

Then, the compact form of the platoon tracking error can be written as

$$\tilde{e}_{k+1} = \begin{cases}(I_N \otimes \mathcal{A})\tilde{e}_k + W \otimes (\mathcal{BK})\tilde{e}_k - W\\ \quad \otimes (\mathcal{BK})\tilde{x}_k + (I_N \otimes \mathcal{A})\bar{d} - \bar{d}, \qquad \delta_k = 1\\ (I_N \otimes \mathcal{A})\tilde{e}_k + W \otimes (\mathcal{BK})\tilde{e}_{k-\tau_k} - W\\ \quad \otimes (\mathcal{BK})\tilde{x}_{k-\tau_k} + (I_N \otimes \mathcal{A})\bar{d} - \bar{d},\ \delta_k = 0\end{cases} \tag{12}$$

with $W = H + Q$. Furthermore, taking $(I_N \otimes A)\bar{d} - \bar{d} = \mathbf{0}$ into consideration, one has

$$\tilde{e}_{k+1} = \begin{cases}(I_N \otimes \mathcal{A})\tilde{e}_k + W \otimes (\mathcal{BK})\tilde{e}_k\\ \qquad - W \otimes (\mathcal{BK})\tilde{x}_k,\ \ \delta_k = 1\\ (I_N \otimes \mathcal{A})\tilde{e}_k + W \otimes (\mathcal{BK})\tilde{e}_{k-\tau_k}\\ \qquad - W \otimes (\mathcal{BK})\tilde{x}_{k-\tau_k},\ \ \delta_k = 0.\end{cases} \tag{13}$$

The platoon performance is related with the matrix W disclosed the complex coupled nature. Because W is a symmetric real matrix, applying the spectral decomposition results in

$$W = V\Theta V^T \tag{14}$$

where the matrices $\Theta = \mathrm{diag}\{\lambda_1, \lambda_2, \ldots, \lambda_N\}$ and V are composed of the eigenvalues λ_i $(i = 1, 2, \ldots, N)$ with $\lambda_1 \le \lambda_2 \le \cdots \le \lambda_N$ and corresponding eigenvectors of W. Then, denoting $e_k = (V^T \otimes I)\tilde{e}_k$, $\bar{x}_k = (V^T \otimes I)\tilde{x}_k$ and $\bar{\xi}_k = (V^T \otimes I)\xi_k$, one has

$$e_{k+1} = \begin{cases}(I_N \otimes \mathcal{A})e_k + \Theta \otimes (\mathcal{BK})e_k\\ \qquad - \Theta \otimes (\mathcal{BK})\bar{x}_k,\ \ \delta_k = 1\\ (I_N \otimes \mathcal{A})e_k + \Theta \otimes (\mathcal{BK})e_{k-\tau_k}\\ \qquad - \Theta \otimes (\mathcal{BK})\bar{x}_{k-\tau_k},\ \ \delta_k = 0.\end{cases} \tag{15}$$

Define $\eta_k = [\bar{x}_k^T\ \bar{\xi}_k^T\ e_k^T]^T$. Then, it follows from (11) and (15) that the augmented closed-loop system is:

$$\eta_{k+1} = \begin{cases}\mathbf{A}_1\eta_k,\ \ \delta_k = 1\\ \mathbf{A}_2\eta_k + \mathbf{B}\eta_{k-\tau_k},\ \ \delta_k = 0\end{cases} \tag{16}$$

where

$$\mathbf{A}_1^{11} = I_N \otimes \mathcal{A} - I_N \otimes \mathcal{L}_1 C$$
$$\mathbf{A}_1^{33} = I_N \otimes \mathcal{A} + \Theta \otimes \mathcal{BK}$$
$$\mathbf{A}_2^{11} = I_N \otimes \mathcal{A} - I_N \otimes \mathcal{L}_1 C$$
$$\mathbf{A}_1 = \begin{bmatrix}\mathbf{A}_1^{11} & -(I_N \otimes \mathcal{L}_2) & 0_{3N\times 3N}\\ I_N \otimes C & \hbar(I_N \otimes I_{n_y}) & 0_{Nn_y\times 3N}\\ -\Theta \otimes (\mathcal{BK}) & 0_{3N\times Nn_y} & \mathbf{A}_1^{33}\end{bmatrix}$$
$$\mathbf{A}_2 = \begin{bmatrix}\mathbf{A}_2^{11} & -(I_N \otimes \mathcal{L}_2) & 0_{3N\times 3N}\\ I_N \otimes C & \hbar(I_N \otimes I_{n_y}) & 0_{Nn_y\times 3N}\\ 0_{3N\times 3N} & 0_{3N\times Nn_y} & I_N \otimes \mathcal{A}\end{bmatrix}$$
$$\mathbf{B} = \begin{bmatrix}0_{3N\times 3N} & 0_{3N\times Nn_y} & 0_{3N\times 3N}\\ 0_{Nn_y\times 3N} & 0_{Nn_y\times Nn_y} & 0_{Nn_y\times 3N}\\ -\Theta \otimes (\mathcal{BK}) & 0_{3N\times Nn_y} & \Theta \otimes (\mathcal{BK})\end{bmatrix}.$$

Remark 1: In this paper, two variables τ_k and δ_k are employed to transform the system suffering from replay attacks into a switched time-delayed one. Such a method is an effective and novel attempt to deal with the challenges of this kind of attack. Furthermore, it is not difficult to understand that the system performance is affected by both the maximum duration of continuous replay attacks and the ratio between duration lengths of active and silent attacks.

Before further discussion, we introduce the following definition, which will be used in the future analysis.

Definition 1: The homogeneous vehicle platoon system (3) with an attacked control protocol (8) under a given undirected communication graph $\mathcal{G}$ is said to achieve the desired platooning control objective with a prescribed constant spacing, if its platoon tracking error dynamics (13) satisfies

$$\lim_{k\to\infty} \|\tilde{e}_k\| = 0, \quad \forall i, j \in \mathcal{V} \tag{17}$$

or equivalently

$$\lim_{k\to\infty} \|e_k\| = 0, \quad \forall i, j \in \mathcal{V} \tag{18}$$

for its transformed dynamics (15).

In summary, the objective of this paper is to design a PIO-based control protocol (7) under replay attacks such that the vehicle platoon (1) with V2V communication topologies satisfying Assumption 1 achieves the formation with given constant inter-vehicle spacing. In other words, the resulting platoon tracking error dynamics (13) satisfies (17) by designing suitable matrix parameters $\mathcal{K}$, $\mathcal{L}_1$ and $\mathcal{L}_2$.

III. Main Results

In this section, the platoon performance is analyzed for a class of homogeneous automated vehicles subject to replay attacks with the help of switched system theories and then the desired PIO-based controller gains are achieved via the solution of certain matrix inequalities. Now, the following lemma is first put forward to the controller design.

Lemma 1 [42]: For the matrix $\mathcal{B}$, there exists a nonsingular matrix N guaranteeing $\mathcal{B}N = P\mathcal{B}$ if the matrix P can be decomposed as

$$P = E^T \begin{bmatrix} P_1 & 0 \\ 0 & P_2 \end{bmatrix} E = E_1^T P_1 E_1 + E_2^T P_2 E_2$$

where $P_1 > 0$ and $P_2 > 0$.

Assumption 3 [43]: For any $k_1 < k_2 \in N$, the number of off/on replay attacks occurring on the interval $[k_1, k_2]$ is denoted by $N(k_1, k_2)$. There exist the chatter bound $N_0 \geq 0$ and the average dwell time (ADT) ϵ_a such that

$$N(k_1, k_2) \leq N_0 + \frac{k_2 - k_1}{\epsilon_a}. \tag{19}$$

Without loss of generality, we choose $N_0 = 0$ in this paper.

Assumption 4: For any $k_1 < k_2 \in N$, the proportion $\varrho_a \in (0, 1]$ of attack active on the interval $[k_1, k_2]$ satisfies

$$\varrho_a > \frac{|\Omega(k_1, k_2)|}{|\Omega(k_1, k_2)| + |\Lambda(k_1, k_2)|}. \tag{20}$$

A. Platoon Performance Analysis

This subsection will provide a sufficient condition to ensure that the augmented closed-loop system (16) is stable via the famous Lyapunov stability theory.

Theorem 1: Consider the vehicle platoon (1) with V2V communication topologies satisfying Assumption 1. Assume that the gain matrices $\mathcal{L}_1$, $\mathcal{L}_2$ and $\mathcal{K}$ in a PIO-based control protocol (7) are predetermined. The vehicles subject to replay attacks achieve the formation with given constant inter-vehicle spacing if there are two positive definite matrices $\mathcal{P}$ and $\mathcal{R}$, and positive scalars $\mu > 1$, $0 < \alpha_0 < \mu\alpha_1$, $0 < \alpha_1 < \mu\alpha_0$, $0 < \kappa < 1$ and $\gamma > 1$ satisfying the following matrix inequalities:

$$\alpha_1 \mathbf{A}_1^T \mathcal{P} \mathbf{A}_1 - \alpha_1(1-\kappa)\mathcal{P} + (m - s + 1)\mathcal{R} < 0 \tag{21}$$

$$\begin{bmatrix} \Pi_{11} & \Pi_{12} \\ \Pi_{21} & \Pi_{22} \end{bmatrix} < 0 \tag{22}$$

and the ADT ϵ_a and the proportion of attack active ϱ_a satisfy

$$\epsilon_a > \epsilon_a^* = \frac{-\ln\mu}{(1-\varrho_a)\ln(1-\kappa) + \varrho_a \ln(1+\gamma)} \tag{23}$$

where

$$\Pi_{11} = \alpha_0 \mathbf{A}_2^T \mathcal{P} \mathbf{A}_2 - \alpha_0(1+\gamma)\mathcal{P} + (m - s + 1)\mathcal{R}$$

$$\Pi_{12} = \alpha_0 \mathbf{A}_2^T \mathcal{P} \mathbf{B}, \ \Pi_{21} = \alpha_0 \mathbf{B}^T \mathcal{P} \mathbf{A}_2$$

$$\Pi_{22} = \alpha_0 \mathbf{B}^T \mathcal{P} \mathbf{B} - (1+\gamma)\mathcal{R}.$$

Proof: According to the discussion in the problem formulation, the addressed platoon analysis is transformed into the stability analysis of the augmented closed-loop system (16). To this end, let us employ the Lyapunov function

$$V_{\delta_k, k} = \alpha_{\delta_k} \eta_k^T \mathcal{P} \eta_k + V_{2k} + V_{3k} \tag{24}$$

with

$$V_{2k} = \sum_{r=k-\tau_k}^{k-1} \eta_r^T \mathcal{R} \eta_r, \ V_{3k} = \sum_{l=k-m+1}^{k-s} \sum_{r=l}^{k-1} \eta_r^T \mathcal{R} \eta_r$$

where $\mathcal{P}$ and $\mathcal{R}$ are two positive definite matrices. Due to the effect from replay attacks, the system (16) is a switching one, and hence the difference of V_k along with such a system has two cases, which will be handled separately.

Case I: The instants $k, k+1 \in \Lambda(k_a, k_b)$, that is, $\delta_k = 1$ and $\delta_{k+1} = 1$.

Calculating the difference of $\alpha_1 \eta_k^T \mathcal{P} \eta_k$ leads to

$$\begin{aligned}
&\alpha_1 \eta_{k+1}^T \mathcal{P} \eta_{k+1} - \alpha_1 \eta_k^T \mathcal{P} \eta_k \\
&= \alpha_1 \{\eta_{k+1}^T \mathcal{P} \eta_{k+1} - \kappa \eta_k^T \mathcal{P} \eta_k - (1-\kappa)\eta_k^T \mathcal{P} \eta_k\} \\
&= \alpha_1 \{(\mathbf{A}_1 \eta_k)^T \mathcal{P} (\mathbf{A}_1 \eta_k) - \kappa \eta_k^T \mathcal{P} \eta_k - (1-\kappa)\eta_k^T \mathcal{P} \eta_k\} \\
&= \eta_k^T (\alpha_1 \mathbf{A}_1^T \mathcal{P} \mathbf{A}_1 - \alpha_1(1-\kappa)\mathcal{P})\eta_k - \kappa\alpha_1 \eta_k^T \mathcal{P} \eta_k.
\end{aligned} \tag{25}$$

Meanwhile, one can obtain the difference of its second and third items

$$\begin{aligned}
\Delta V_{2k} &= V_{2,k+1} - V_{2k} \\
&= \sum_{r=k-\tau_{k+1}+1}^{k} \eta_r^T \mathcal{R} \eta_r - (1-\kappa) \sum_{r=k-\tau_k}^{k-1} \eta_r^T \mathcal{R} \eta_r \\
&\quad - \kappa \sum_{r=k-\tau_k}^{k-1} \eta_r^T \mathcal{R} \eta_r \\
&= \eta_k^T \mathcal{R} \eta_k + \sum_{r=k-\tau_{k+1}+1}^{k-1} \eta_r^T \mathcal{R} \eta_r \\
&\quad - (1-\kappa) \sum_{r=k-\tau_k}^{k-1} \eta_r^T \mathcal{R} \eta_r - \kappa \sum_{r=k-\tau_k}^{k-1} \eta_r^T \mathcal{R} \eta_r \\
&= \eta_k^T \mathcal{R} \eta_k - (1-\kappa)\eta_{k-\tau_k}^T \mathcal{R} \eta_{k-\tau_k} \\
&\quad - (1-\kappa) \sum_{r=k-\tau_k+1}^{k-1} \eta_r^T \mathcal{R} \eta_r \\
&\quad + \sum_{r=k-\tau_{k+1}+1}^{k-1} \eta_r^T \mathcal{R} \eta_r - \kappa \sum_{r=k-\tau_k}^{k-1} \eta_r^T \mathcal{R} \eta_r \\
&= \eta_k^T \mathcal{R} \eta_k - (1-\kappa)\eta_{k-\tau_k}^T \mathcal{R} \eta_{k-\tau_k}
\end{aligned}$$

$$
\begin{aligned}
&+\sum_{r=k-s+1}^{k-1}\eta_r^T\mathcal{R}\eta_r+\sum_{r=k-\tau_{k+1}+1}^{k-s}\eta_r^T\mathcal{R}\eta_r\\
&-(1-\kappa)\sum_{r=k-\tau_k+1}^{k-1}\eta_r^T\mathcal{R}\eta_r-\kappa\sum_{r=k-\tau_k}^{k-1}\eta_r^T\mathcal{R}\eta_r\\
\le{}&\eta_k^T\mathcal{R}\eta_k-(1-\kappa)\eta_{k-\tau_k}^T\mathcal{R}\eta_{k-\tau_k}\\
&+\sum_{r=k-m+1}^{k-s}\eta_r^T\mathcal{R}\eta_r-\kappa\sum_{r=k-\tau_k}^{k-1}\eta_r^T\mathcal{R}\eta_r
\end{aligned}\tag{26}
$$

and

$$
\begin{aligned}
\Delta V_{3k}={}&V_{3,k+1}-V_{3k}\\
={}&\sum_{l=k-m+2}^{k-s+1}\sum_{r=l}^{k}\eta_r^T\mathcal{R}\eta_r-(1-\kappa)\sum_{l=k-m+1}^{k-s}\sum_{r=l}^{k-1}\eta_r^T\mathcal{R}\eta_r\\
&-\kappa\sum_{l=k-m+1}^{k-s}\sum_{r=l}^{k-1}\eta_r^T\mathcal{R}\eta_r\\
={}&\sum_{l=k-m+1}^{k-s}\sum_{r=l+1}^{k}\eta_r^T\mathcal{R}\eta_r-(1-\kappa)\sum_{l=k-m+1}^{k-s}\sum_{r=l}^{k-1}\eta_r^T\mathcal{R}\eta_r\\
&-\kappa\sum_{l=k-m+1}^{k-s}\sum_{r=l}^{k-1}\eta_r^T\mathcal{R}\eta_r\\
={}&\sum_{l=k-m+1}^{k-s}(\eta_k^T\mathcal{R}\eta_k-\eta_l^T\mathcal{R}\eta_l+\kappa\sum_{r=l}^{k-1}\eta_r^T\mathcal{R}\eta_r)\\
&-\kappa\sum_{l=k-m+1}^{k-s}\sum_{r=l}^{k-1}\eta_r^T\mathcal{R}\eta_r\\
\le{}&(m-s)\eta_k^T\mathcal{R}\eta_k-\sum_{r=k-m+1}^{k-s}\eta_r^T\mathcal{R}\eta_r\\
&-\kappa\sum_{l=k-m+1}^{k-s}\sum_{r=l}^{k-1}\eta_r^T\mathcal{R}\eta_r.
\end{aligned}\tag{27}
$$

Synthesizing (25)–(27), one has

$$
\begin{aligned}
\Delta V_{1,k}\le{}&\eta_k^T(\alpha_1\mathbf{A}_1^T\mathcal{P}\mathbf{A}_1-\alpha_1(1-\kappa)\mathcal{P})\eta_k\\
&+(m-s+1)\eta_k^T\mathcal{R}\eta_k\\
&-(1-\kappa)\eta_{k-\tau_k}^T\mathcal{R}\eta_{k-\tau_k}-\kappa\alpha_1\eta_k^T\mathcal{P}\eta_k\\
&-\kappa\sum_{r=k-\tau_k}^{k-1}\eta_r^T\mathcal{R}\eta_r-\kappa\sum_{l=k-m+1}^{k-s}\sum_{r=l}^{k-1}\eta_r^T\mathcal{R}\eta_r\\
={}&\eta_k^T(\alpha_1\mathbf{A}_1^T\mathcal{P}\mathbf{A}_1-\alpha_1(1-\kappa)\mathcal{P}+(m-s+1)\mathcal{R})\eta_k\\
&-(1-\kappa)\eta_{k-\tau_k}^T\mathcal{R}\eta_{k-\tau_k}-\kappa V_{1,k}
\end{aligned}\tag{28}
$$

which means

$$
V_{1,k+1}\le(1-\kappa)V_{1,k}.\tag{29}
$$

Case II: The instants k, $k+1\in\Omega(k_a,k_b)$, that is, $\delta_k=0$ and $\delta_{k+1}=0$.

Similarly, taking the difference of the first item in $V_{\delta_k,k}$ along with the system (16) results in

$$
\begin{aligned}
&\alpha_0\eta_{k+1}^T\mathcal{P}\eta_{k+1}-\alpha_0\eta_k^T\mathcal{P}\eta_k\\
={}&\alpha_0\{(\mathbf{A}_2\eta_k+\mathbf{B}\eta_{k-\tau_k})^T\mathcal{P}(\mathbf{A}_2\eta_k+\mathbf{B}\eta_{k-\tau_k})\\
&+\gamma\eta_k^T\mathcal{P}\eta_k-(1+\gamma)\eta_k^T\mathcal{P}\eta_k\}\\
={}&\alpha_0\{\eta_k^T\mathbf{A}_2^T\mathcal{P}\mathbf{A}_2\eta_k+\eta_k^T\mathbf{A}_2^T\mathcal{P}\mathbf{B}\eta_{k-\tau_k}\\
&+\eta_{k-\tau_k}^T\mathbf{B}^T\mathcal{P}\mathbf{A}_2\eta_k+\eta_{k-\tau_k}^T\mathbf{B}^T\mathcal{P}\mathbf{B}\eta_{k-\tau_k}\\
&+\gamma\eta_k^T\mathcal{P}\eta_k-(1+\gamma)\eta_k^T\mathcal{P}\eta_k\}\\
={}&\eta_k^T(\alpha_0\mathbf{A}_2^T\mathcal{P}\mathbf{A}_2-\alpha_0(1+\gamma)\mathcal{P})\eta_k+\alpha_0\eta_k^T\mathbf{A}_2^T\mathcal{P}\mathbf{B}\eta_{k-\tau_k}\\
&+\alpha_0\eta_{k-\tau_k}^T\mathbf{B}^T\mathcal{P}\mathbf{A}_2\eta_k+\alpha_0\eta_{k-\tau_k}^T\mathbf{B}^T\mathcal{P}\mathbf{B}\eta_{k-\tau_k}\\
&+\gamma\alpha_0\eta_k^T\mathcal{P}\eta_k.
\end{aligned}\tag{30}
$$

Meanwhile, one can obtain the difference of its second and third items

$$
\begin{aligned}
\Delta V_{2k}={}&\sum_{r=k-\tau_{k+1}+1}^{k}\eta_r^T\mathcal{R}\eta_r-(1+\gamma)\sum_{r=k-\tau_k}^{k-1}\eta_r^T\mathcal{R}\eta_r\\
&+\gamma\sum_{r=k-\tau_k}^{k-1}\eta_r^T\mathcal{R}\eta_r\\
\le{}&\eta_k^T\mathcal{R}\eta_k-(1+\gamma)\eta_{k-\tau_k}^T\mathcal{R}\eta_{k-\tau_k}\\
&+\sum_{r=k-m+1}^{k-s}\eta_r^T\mathcal{R}\eta_r+\gamma\sum_{r=k-\tau_k}^{k-1}\eta_r^T\mathcal{R}\eta_r.
\end{aligned}\tag{31}
$$

and

$$
\begin{aligned}
\Delta V_{3k}={}&\sum_{l=k-m+2}^{k-s+1}\sum_{r=l}^{k}\eta_r^T\mathcal{R}\eta_r-(1+\gamma)\sum_{l=k-m+1}^{k-s}\sum_{r=l}^{k-1}\eta_r^T\mathcal{R}\eta_r\\
&+\gamma\sum_{l=k-m+1}^{k-s}\sum_{r=l}^{k-1}\eta_r^T\mathcal{R}\eta_r\\
\le{}&(m-s)\eta_k^T\mathcal{R}\eta_k-\sum_{r=k-m+1}^{k-s}\eta_r^T\mathcal{R}\eta_r\\
&+\gamma\sum_{l=k-m+1}^{k-s}\sum_{r=l}^{k-1}\eta_r^T\mathcal{R}\eta_r.
\end{aligned}\tag{32}
$$

Synthesizing (30)–(32), one has

$$
\begin{aligned}
\Delta V_{0,k}\le{}&\eta_k^T(\alpha_0\mathbf{A}_2^T\mathcal{P}\mathbf{A}_2-\alpha_0(1+\gamma)\mathcal{P})\eta_k+\alpha_0\eta_k^T\mathbf{A}_2^T\mathcal{P}\mathbf{B}\eta_{k-\tau_k}\\
&+\alpha_0\eta_{k-\tau_k}^T\mathbf{B}^T\mathcal{P}\mathbf{A}_2\eta_k+\alpha_0\eta_{k-\tau_k}^T\mathbf{B}^T\mathcal{P}\mathbf{B}\eta_{k-\tau_k}\\
&+\eta_k^T\mathcal{R}\eta_k-(1+\gamma)\eta_{k-\tau_k}^T\mathcal{R}\eta_{k-\tau_k}\\
&+\sum_{r=k-m+1}^{k-s}\eta_r^T\mathcal{R}\eta_r+(m-s)\eta_k^T\mathcal{R}\eta_k\\
&-\sum_{r=k-m+1}^{k-s}\eta_r^T\mathcal{R}\eta_r+\gamma\eta_k^T\mathcal{P}\eta_k
\end{aligned}
$$

$$
\begin{aligned}
&+\gamma\sum_{r=k-\tau_k}^{k-1}\eta_r^T\mathcal{R}\eta_r+\gamma\sum_{l=k-m+1}^{k-s}\sum_{r=l}^{k-1}\eta_r^T\mathcal{R}\eta_r\\
&=\eta_k^T(\alpha_0\mathbf{A}_2^T\mathcal{P}\mathbf{A}_2-\alpha_0(1+\gamma)\mathcal{P}+(m-s+1)\mathcal{R})\eta_k\\
&\quad+\eta_{k-\tau_k}^T(\alpha_0\mathbf{B}^T\mathcal{P}\mathbf{B}-(1+\gamma)\mathcal{R})\eta_{k-\tau_k}\\
&\quad+\alpha_0\eta_k^T\mathbf{A}_2^T\mathcal{P}\mathbf{B}\eta_{k-\tau_k}+\alpha_0\eta_{k-\tau_k}^T\mathbf{B}^T\mathcal{P}\mathbf{A}_2\eta_k+\gamma V_{0,k}\\
&=\zeta_k^T\Pi\zeta_k+\gamma V_{0,k}
\end{aligned}\tag{33}
$$

where

$$
\zeta_t=[\ \eta_k^T\quad \eta_{k-\tau_k}^T\ ]^T
$$

$$
\Pi=\begin{bmatrix}\Pi_{11} & \Pi_{12}\\ \Pi_{21} & \Pi_{22}\end{bmatrix}.
$$

Furthermore, it follows from the above inequality that:

$$
V_{0,k+1}\le(1+\gamma)V_{0,k}. \tag{34}
$$

In what follows, let us investigate the stability of the augmented closed-loop system (16). Without loss of generality, we assume that the switching instants are $k_a<k_0<k_1<k_2<\cdots<k_{l-1}<k_l<k<k_b$ in $\Omega(k_a,k_b)\cup\Lambda(k_a,k_b)$. If $\delta_k=0$, it is easy from (29) and (34) to deduce that

$$
\begin{aligned}
V_{0,k}&\le(1+\gamma)^{k-k_l}V_{0,k_l}\\
&\le\mu(1+\gamma)^{k-k_l}V_{1,k_l}\\
&\le\mu^2(1+\gamma)^{k-k_l}(1-\kappa)^{k_l-k_{l-1}}V_{1,k_{l-1}}\\
&\le\cdots\\
&\le\mu^{N(k_a,k)}(1+\gamma)^{|\Omega(k_a,k)|}(1-\kappa)^{|\Lambda(k_a,k)|}V_{\delta_{k_a},k_a}.
\end{aligned}\tag{35}
$$

Similarly, if $\delta_k=1$, one has

$$
\begin{aligned}
V_{1,k}&\le(1-\kappa)^{k-k_l}V_{1,k_l}\\
&\le\mu(1-\kappa)^{k-k_l}V_{0,k_l}\\
&\le\mu^2(1-\kappa)^{k-k_l}(1+\gamma)^{k_l-k_{l-1}}V_{0,k_{l-1}}\\
&\le\cdots\\
&\le\mu^{N(k_a,k)}(1-\kappa)^{|\Lambda(k_a,k)|}(1+\gamma)^{|\Omega(k_a,k)|}V_{\delta_{k_a},k_a}.
\end{aligned}\tag{36}
$$

After that, synthesizing (35) and (36) results in

$$
\begin{aligned}
V_{\delta_k,k}\le\ &\mu^{N(k_a,k)}(1-\kappa)^{|\Lambda(k_a,k)|}\\
&\times(1+\gamma)^{|\Omega(k_a,k)|}V_{\delta_{k_a},k_a}.
\end{aligned}
$$

In order to guarantee the stability of the closed-loop system (16), the following condition is needed:

$$
\mu^{N(k_a,k)}(1-\kappa)^{|\Lambda(k_a,k)|}(1+\gamma)^{|\Omega(k_a,k)|}<1
$$

which means

$$
\mu^{\frac{|\Lambda(k_a,k)|}{\epsilon_a}}(1-\kappa)^{|\Lambda(k_a,k)|}\mu^{\frac{|\Omega(k_a,k)|}{\epsilon_a}}(1+\gamma)^{|\Omega(k_a,k)|}<1.
$$

Noting the definition of the ADT ϵ_a and the proportion ϱ_a, we have

$$
\begin{aligned}
V_{\delta_k,k}&\le(\mu^{1/\epsilon_a}(1-\kappa))^{|\Lambda(k_a,k)|}(\mu^{1/\epsilon_a}(1+\gamma))^{|\Omega(k_a,k)|}V_{\delta_{k_a},k_a}\\
&<V_{\delta_{k_a},k_a}
\end{aligned}
$$

if

$$
\frac{|\Omega(k_a,k)|}{|\Lambda(k_a,k)|}<\frac{\varrho_a}{1-\varrho_a}<-\frac{1/\epsilon_a\ln\mu+\ln(1-\kappa)}{1/\epsilon_a\ln\mu+\ln(1+\gamma)}.
$$

Finally, considering the ADT and the relationship between the closed-loop system (16) and the platoon tracking error dynamics (13), one has that the desired platoon performance is achieved, which completes the proof. ■

It is worth noting that the PIO-based control scheme (7) proposed in this paper is quite general. Specifically, if $\mathcal{L}_2=0$, the proposed controller will be degenerated into a traditional observer-based one. As such, a corollary about Theorem 1 is provided as follows.

Corollary 1: Consider the vehicle platoon (1) with V2V communication topologies satisfying Assumption 1. When $\mathcal{L}_2=0$, assume that the gain matrices $\mathcal{L}_1$ and $\mathcal{K}$ in an observer-based control protocol (7) are predetermined. The vehicles subject to replay attacks achieve the formation with given constant inter-vehicle spacing if there are two positive definite matrices $\tilde{\mathcal{P}}$ and $\tilde{\mathcal{R}}$, and positive scalars $\mu>1$, $0<\alpha_0<\mu\alpha_1$, $0<\alpha_1<\mu\alpha_0$, $0<\kappa<1$ and $\gamma>1$ satisfying the following matrix inequalities:

$$
\alpha_1\mathbf{A}_3^T\tilde{\mathcal{P}}\mathbf{A}_3-\alpha_1(1-\kappa)\tilde{\mathcal{P}}+(m-s+1)\tilde{\mathcal{R}}<0 \tag{37}
$$

$$
\begin{bmatrix}\Upsilon_{11} & \Upsilon_{12}\\ \Upsilon_{21} & \Upsilon_{22}\end{bmatrix}<0 \tag{38}
$$

and the ADT ϵ_a and the proportion of attack active ϱ_a satisfy

$$
\epsilon_a>\epsilon_a^*=\frac{-\ln\mu}{(1-\varrho_a)\ln(1-\kappa)+\varrho_a\ln(1+\gamma)}
$$

where

$$
\begin{aligned}
&\Upsilon_{11}=\alpha_0\mathbf{A}_4^T\tilde{\mathcal{P}}\mathbf{A}_4-\alpha_0(1+\gamma)\tilde{\mathcal{P}}+(m-s+1)\tilde{\mathcal{R}}\\
&\Upsilon_{12}=\alpha_0\mathbf{A}_4^T\tilde{\mathcal{P}}\tilde{\mathbf{B}},\ \Pi_{21}=\alpha_0\tilde{\mathbf{B}}^T\tilde{\mathcal{P}}\mathbf{A}_4\\
&\Upsilon_{22}=\alpha_0\tilde{\mathbf{B}}^T\tilde{\mathcal{P}}\tilde{\mathbf{B}}-(1+\gamma)\tilde{\mathcal{R}}\\
&\mathbf{A}_3=\begin{bmatrix}I_N\otimes\mathcal{A}-I_N\otimes\mathcal{L}_1C & 0_{3N\times3N}\\ -\Theta\otimes(\mathcal{B}\mathcal{K}) & I_N\otimes\mathcal{A}+\Theta\otimes\mathcal{B}\mathcal{K}\end{bmatrix}\\
&\mathbf{A}_4=\begin{bmatrix}I_N\otimes\mathcal{A}-I_N\otimes\mathcal{L}_1C & 0_{3N\times3N}\\ 0_{3N\times3N} & I_N\otimes\mathcal{A}\end{bmatrix}\\
&\tilde{\mathbf{B}}=\begin{bmatrix}0_{3N\times3N} & 0_{3N\times3N}\\ -\Theta\otimes(\mathcal{B}\mathcal{K}) & \Theta\otimes(\mathcal{B}\mathcal{K})\end{bmatrix}.
\end{aligned}
$$

B. Observer-Based Controller Design

In the above subsection, a sufficient condition has been developed to guarantee the desired platoon performance. In this subsection, a set of solvable conditions will be proposed to obtain the PIO-based controller gains.

Theorem 2: Consider the vehicle platoon (1) with V2V communication topologies satisfying Assumption 1. If there are five positive definite matrices P_1, P_2, P_{31}, P_{32} and R, three matrices $\bar{\mathcal{L}}_1$, $\bar{\mathcal{L}}_2$ and $\bar{\mathcal{K}}$, positive scalars $\mu>1$, $0<\alpha_0<\mu\alpha_1$, $0<\alpha_1<\mu\alpha_0$, $0<\kappa<1$ and $\gamma>1$ such that, for $i\in\{1,N\}$, the following matrix inequalities:

$$
\Xi_{1i}=\begin{bmatrix}-\alpha_1(1-\kappa)P+(m-s+1)R & *\\ \Psi_i & -\alpha_1P\end{bmatrix}<0 \tag{39}
$$

and

$$\Xi_{2i} = \begin{bmatrix} \bar{\Pi}_{11} & * & * \\ 0 & -(1+\gamma)R & * \\ \bar{\Pi}_{31} & \bar{\Pi}_{32i} & -\alpha_0 P \end{bmatrix} < 0 \tag{40}$$

hold, where

$$P = \mathrm{diag}\{P_1, P_2, P_3\},\ P_3 = E_1^T P_{31} E_1 + E_2^T P_{32} E_2$$

$$\Psi_i = \alpha_1 \begin{bmatrix} P_1\mathcal{A} - \bar{\mathcal{L}}_1 C & -\bar{\mathcal{L}}_2 & 0 \\ P_2 C & \hbar P_2 & 0 \\ -\lambda_i \mathcal{B}\bar{\mathcal{K}} & 0 & P_3\mathcal{A} + \lambda_i \mathcal{B}\bar{\mathcal{K}} \end{bmatrix}$$

$$\bar{\Pi}_{11} = -\alpha_0(1+\gamma)P + (m-s+1)R$$

$$\bar{\Pi}_{31} = \alpha_0 \begin{bmatrix} P_1\mathcal{A} - \bar{\mathcal{L}}_1 C & -\bar{\mathcal{L}}_2 & 0 \\ P_2 C & \hbar P_2 & 0 \\ 0 & 0 & P_3\mathcal{A} \end{bmatrix}$$

$$\bar{\Pi}_{32i} = \alpha_0 \begin{bmatrix} 0 & 0 & 0 \\ 0 & 0 & 0 \\ -\lambda_i \mathcal{B}\bar{\mathcal{K}} & 0 & \lambda_i \mathcal{B}\bar{\mathcal{K}} \end{bmatrix}$$

then the vehicles with a PIO-based control protocol (7) with the gains given by $\mathcal{L}_1 = P_1^{-1}\bar{\mathcal{L}}_1$, $\mathcal{L}_2 = P_1^{-1}\bar{\mathcal{L}}_2$, and $\mathcal{K} = F\Delta^{-1}P_{31}^{-1}\Delta F^T\bar{\mathcal{K}}$ achieve the formation with given constant inter-vehicle spacing. Furthermore, and the ADT ϵ_a and the proportion of attack active ϱ_a satisfy

$$\epsilon_a > \epsilon_a^* = \frac{-\ln\mu}{(1-\varrho_a)\ln(1-\kappa) + \varrho_a \ln(1+\gamma)}.$$

Proof: Note that the matrices in (21) and (22) are block diagonal if selecting $\mathcal{P} = \mathrm{diag}\{I\otimes P_1, I\otimes P_2, I\otimes P_3\}$ and $\mathcal{R} = I\otimes R$, and thus such two inequalities can be reorganized as follows:

$$\alpha_1 \mathbf{A}_{1i}^T P \mathbf{A}_{1i} - \alpha_1(1-\kappa)P + (m-s+1)R < 0 \tag{41}$$

and

$$\begin{bmatrix} \Pi_{11} & \Pi_{12i} \\ \Pi_{21i} & \Pi_{22i} \end{bmatrix} < 0 \tag{42}$$

for $i = 1, 2, \ldots, N$, where

$$\mathbf{A}_{1i} = \begin{bmatrix} \mathcal{A} - \mathcal{L}_1 C & -\mathcal{L}_2 & 0 \\ C & \hbar I & 0 \\ -\lambda_i \mathcal{B}\mathcal{K} & 0 & \mathcal{A} + \lambda_i \mathcal{B}\mathcal{K} \end{bmatrix}$$

$$\mathbf{A}_2 = \begin{bmatrix} \mathcal{A} - \mathcal{L}_1 C & -\mathcal{L}_2 & 0 \\ C & \hbar I & 0 \\ 0 & 0 & \mathcal{A} \end{bmatrix}$$

$$\mathbf{B}_i = \begin{bmatrix} 0 & 0 & 0 \\ 0 & 0 & 0 \\ -\lambda_i \mathcal{B}\mathcal{K} & 0 & \lambda_i \mathcal{B}\mathcal{K} \end{bmatrix}$$

$$\Pi_{11} = \alpha_0 \mathbf{A}_2^T P \mathbf{A}_2 - \alpha_0(1+\gamma)P + (m-s+1)R$$

$$\Pi_{12i} = \alpha_0 \mathbf{A}_2^T P \mathbf{B}_i,\ \Pi_{21i} = \alpha_0 \mathbf{B}_i^T P \mathbf{A}_2$$

$$\Pi_{22i} = \alpha_0 \mathbf{B}_i^T P \mathbf{B}_i - (1+\gamma)R.$$

By resorting to the Schur complement lemma, the above inequalities are true if and only if

$$\begin{bmatrix} -\alpha_1(1-\kappa)P + (m-s+1)R & * \\ \mathbf{A}_{1i} & -(\alpha_1 P)^{-1} \end{bmatrix} < 0 \tag{43}$$

and

$$\begin{bmatrix} \bar{\Pi}_{11} & 0 & * \\ 0 & -(1+\gamma)R & * \\ \mathbf{A}_2 & \mathbf{B}_i & -(\alpha_0 P)^{-1} \end{bmatrix} < 0 \tag{44}$$

where

$$\bar{\Pi}_{11} = -\alpha_0(1+\gamma)P + (m-s+1)R.$$

In what follows, by pre-multiplying and post-multiplying (43) and (44) by $\mathrm{diag}\{I, \alpha_1 P\}$ and $\mathrm{diag}\{I, I, \alpha_0 P\}$ and their transpose, one cannot difficultly obtain:

$$\begin{bmatrix} -\alpha_1(1-\kappa)P + (m-s+1)R & * \\ \alpha_1 P\mathbf{A}_{1i} & -\alpha_1 P \end{bmatrix} < 0 \tag{45}$$

and

$$\begin{bmatrix} \bar{\Pi}_{11} & 0 & * \\ 0 & -(1+\gamma)R & * \\ \alpha_0 P\mathbf{A}_2 & \alpha_0 P\mathbf{B}_i & -\alpha_0 P \end{bmatrix} < 0. \tag{46}$$

To obtain the desired gains, we first choose the structure $P = \mathrm{diag}\{P_1, P_2, P_3\}$ and then have

$$P\mathbf{A}_{1i} = \begin{bmatrix} P_1\mathcal{A} - P_1\mathcal{L}_1 C & -P_1\mathcal{L}_2 & 0 \\ P_2 C & \hbar P_2 & 0 \\ -\lambda_i P_3\mathcal{B}\mathcal{K} & 0 & P_3\mathcal{A} + \lambda_i P_3\mathcal{B}\mathcal{K} \end{bmatrix}$$

$$P\mathbf{B}_i = \begin{bmatrix} 0 & 0 & 0 \\ 0 & 0 & 0 \\ -\lambda_i P_3\mathcal{B}\mathcal{K} & 0 & \lambda_i P_3\mathcal{B}\mathcal{K} \end{bmatrix}.$$

It should be pointed out that both $P\mathbf{A}_{1i}$ and $P\mathbf{B}_i$ in the above two inequalities contain the nonlinear term $P_3\mathcal{B}\mathcal{K}$, which makes it difficult to be solved and obtain controller parameters. Since $\mathcal{B}$ is of column full ranks, by means of Lemma 1, one has that there exist two matrices $P_{31} > 0$ and $P_{32} > 0$ and a nonsingular matrix $\aleph$ such that $P_3 = E_1^T P_{31} E_1 + E_2^T P_{32} E_2$, and $P_3\mathcal{B} = \mathcal{B}\aleph$.

Letting $\aleph\mathcal{K} = \bar{\mathcal{K}}$, $P_1\mathcal{L}_1 = \bar{\mathcal{L}}_1$ and $P_1\mathcal{L}_2 = \bar{\mathcal{L}}_2$, one has that (45) and (46) are true if (39) and (40) hold for $i = 1, 2, \ldots, N$. In what follows, due to $\lambda_1 \le \lambda_i \le \lambda_N$, there exists a scalar $\varsigma_i \in [0,1]$ such that $\lambda_i = \varsigma_i\lambda_1 + (1-\varsigma_i)\lambda_N$. Furthermore, one has

$$\Xi_{1i} = \varsigma_i \Xi_{11} + (1-\varsigma_i)\Xi_{1N}$$
$$\Xi_{2i} = \varsigma_i \Xi_{21} + (1-\varsigma_i)\Xi_{2N}.$$

Hence, it can be deduced from $\Xi_{11} < 0$, $\Xi_{1N} < 0$, $\Xi_{21} < 0$ and $\Xi_{2N} < 0$ that (45) and (46) are also true.

Finally, further considering the relationship $P_3\mathcal{B}\mathcal{K} = \mathcal{B}\aleph\mathcal{K}$, that is,

$$P_3 E^T \begin{bmatrix} \Delta \\ 0 \end{bmatrix} F^T \mathcal{K} = E^T \begin{bmatrix} \Delta \\ 0 \end{bmatrix} F^T \aleph\mathcal{K} \tag{47}$$

one has $P_{31}\Delta F^T\mathcal{K} = \Delta F^T\aleph\mathcal{K} = \Delta F^T\bar{\mathcal{K}}$, which means $\mathcal{K} =$

$F\Delta^{-1}P_{31}^{-1}\Delta F^T\tilde{\mathcal{K}}$. ■

Corresponding to the analysis result in Corollary 1, one has the following design condition about the desired gains.

Corollary 2: Consider the vehicle platoon (1) with V2V communication topologies satisfying Assumption 1. When $\mathcal{L}_2 = 0$, if there are four positive definite matrices $\tilde{P}_1$, $\tilde{P}_{31}$, $\tilde{P}_{32}$ and $\tilde{R}$, two matrices $\tilde{\mathcal{L}}_1$ and $\tilde{\mathcal{K}}$, positive scalars $\mu > 1$, $0 < \alpha_0 < \mu\alpha_1$, $0 < \alpha_1 < \mu\alpha_0$, $0 < \kappa < 1$ and $\gamma > 1$ such that, for $i \in \{1, N\}$, the following matrix inequalities:

$$\Xi_{3i} = \begin{bmatrix} -\alpha_1(1-\kappa)\tilde{P} + (m-s+1)\tilde{\mathcal{R}} & * \\ \Psi_i & -\alpha_1\tilde{P} \end{bmatrix} < 0 \quad (48)$$

and

$$\Xi_{4i} = \begin{bmatrix} \bar{\Upsilon}_{11} & * & * \\ 0 & -(1+\gamma)\tilde{R} & * \\ \bar{\Upsilon}_{31} & \bar{\Upsilon}_{32i} & -\alpha_0\tilde{P} \end{bmatrix} < 0 \quad (49)$$

hold, where

$$\tilde{P} = \mathrm{diag}\{\tilde{P}_1, \tilde{P}_3\},\ \tilde{P}_3 = E_1^T\tilde{P}_{31}E_1 + E_2^T\tilde{P}_{32}E_2$$

$$\Psi_i = \alpha_1\begin{bmatrix} \tilde{P}_1\mathcal{A} - \tilde{\mathcal{L}}_1C & 0 \\ -\lambda_i\mathcal{B}\tilde{\mathcal{K}} & \tilde{P}_3\mathcal{A} + \lambda_i\mathcal{B}\tilde{\mathcal{K}} \end{bmatrix}$$

$$\bar{\Upsilon}_{11} = -\alpha_0(1+\gamma)\tilde{P} + (m-s+1)\tilde{R}$$

$$\bar{\Upsilon}_{31} = \alpha_0\begin{bmatrix} \tilde{P}_1\mathcal{A} - \tilde{\mathcal{L}}_1C & 0 \\ 0 & \tilde{P}_3\mathcal{A} \end{bmatrix}$$

$$\bar{\Upsilon}_{32i} = \alpha_0\begin{bmatrix} 0 & 0 \\ -\lambda_i\mathcal{B}\tilde{\mathcal{K}} & \lambda_i\mathcal{B}\tilde{\mathcal{K}} \end{bmatrix}$$

then the vehicles with an observer-based control protocol (7) with the gains given by $\mathcal{L}_1 = \tilde{P}_1^{-1}\tilde{\mathcal{L}}_1$ and $\mathcal{K} = F\Delta^{-1}\tilde{P}_{31}^{-1}\Delta F^T\tilde{\mathcal{K}}$ achieve the formation with given constant inter-vehicle spacing. Furthermore, and the ADT ϵ_a and the proportion of attack active ϱ_a satisfy

$$\epsilon_a > \epsilon_a^* = \frac{-\ln\mu}{(1-\varrho_a)\ln(1-\kappa) + \varrho_a\ln(1+\gamma)}.$$

Remark 2: From the defenders' perspective, the designed controller should defend against continuous attacks with a longer duration, in other words, the security of controlled systems is high. As discussed in the problem formulation, the influence of replay attacks is disclosed by a time-delayed signal τ_k, and the maximum duration of continuous replay attacks is the same with the induced duration occurring time-delays. Generally speaking, the actual upper bound of replay attacks is unknown, and cannot be accurately obtained by defenders. As such, the developed approach is conservative and robust. From the viewpoint of defenders, the defender with the designed controller can receive a tolerable worst attack cases by optimizing the value of $m-s$ and m, corresponding to the attack duration and the delay of recorded historical data. As such, one has the following multi-objective optimization problem with the priority ϖ_1 and ϖ_2 solvable:

$$\max\ \varpi_1(m-s) + \varpi_2 m$$
$$\text{s.t. } (39), (40).$$

Finally, it is not difficult to see from Theorem 1 that the solvability of matrix inequalities is dependent on the time interval of the attack-active duration "$m-s+1$". Particularly, the larger the time interval, the smaller the solvability.

Remark 3: So far, we have established a distributed PIO-based control scheme for a class of connected automated vehicles subject to replay attacks. The feasibility of the vehicles' platoon has been transformed into the solvability of a set of matrix inequalities only related to the minimum and maximum eigenvalues of communication topologies. As such, the developed result is independent of the number of vehicles and hence satisfies the scalability requirement.

IV. Simulation Results

In this section, a vehicle platoon composed of one leader (labeled as 0) and three followers (labeled as 1, 2, 3) is presented to validate the effectiveness of the proposed PIO-based control protocol. The simulation duration is set as 100 s, and the desired spacing between front and rear vehicles during platoon driving is set as 10 m.

A. Simulation Scenarios and Gain Design

The configuration of the vehicle platoon is shown in Fig. 1. The time-delayed parameter π in the powertrain systems is assumed to be 0.5. The Laplacian matrix H related to the V2V communication topology among three following vehicles is chosen as:

$$H = \begin{bmatrix} 0.5 & -0.5 & 0 \\ -0.5 & 1 & -0.5 \\ 0 & -0.5 & 0.5 \end{bmatrix}$$

and the pinning matrix is $Q = \mathrm{diag}\{1, 0, 1\}$. Finally, the measurement matrix is $C = [1\ \ -1\ \ 0]$.

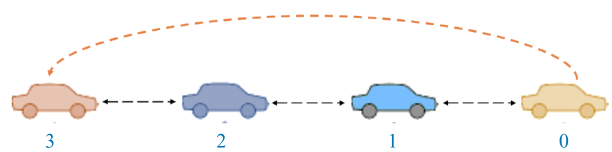


Fig. 1. Vehicle platoon configuration.

In what follows, the sampling period h, forgetting parameter $\hbar$, and the positive constants κ, γ, α_0 and α_1 are taken as $1s$, 0.8, 0.005, 5, 0.01 and 1.3, respectively. With the help of the MATLAB software with Sedumi toolboxes, the satisfied gains of PIO-based controllers are as follows:

$$\mathcal{L}_1 = \begin{bmatrix} 1.7127 & 0.3557 & -0.0018 \end{bmatrix}^T$$

$$\mathcal{L}_2 = \begin{bmatrix} -0.0047 & -0.0016 & 0.0008 \end{bmatrix}^T$$

$$\mathcal{K} = \begin{bmatrix} -0.1134 & -0.4675 & -0.1862 \end{bmatrix}.$$

B. Simulation Results

In this simulation, the initial states of the leader vehicle and three following vehicles are set as $x_0 = [\,50\ 5\ 0\,]^T$, $x_1 = [\,20\ 5.8\ 0\,]^T$, $x_2 = [\,10\ 6.4\ 0\,]^T$ and $x_3 = [\,0\ 7.8\ 0\,]^T$, respectively. Furthermore, the replay attacks is continuously occurred from $15s$ to $21s$, and the duration of each replay attack is $7s$ (that is $m = 7$ and $s = 1$).

The simulation results are deployed in Figs. 2–4. Specifically, Fig. 2 shows the state trajectories of x_i $(i = 0, 1, 2, 3)$ with the PIO-based controller and Fig. 3 shows the trajectories of open-loop cases. Compared to these figures, we cannot difficultly see that the position spacing of each vehicle can be guaranteed, and the velocity of each vehicle converges to the leader's velocity $v_0 = 5$ m/s. As such, the formation with the given safety spacing can be achieved, which demonstrates the effectiveness of the proposed control scheme. Fig. 4(a) plots the spacing errors among vehicles, that satisfy the space requirement (i.e., no more than 10 m) within the initial adjustment stage. This further verifies the safety of all vehicles when at the wheel. Fig. 4(b) provides the velocity errors among vehicles, which will converge to zero.

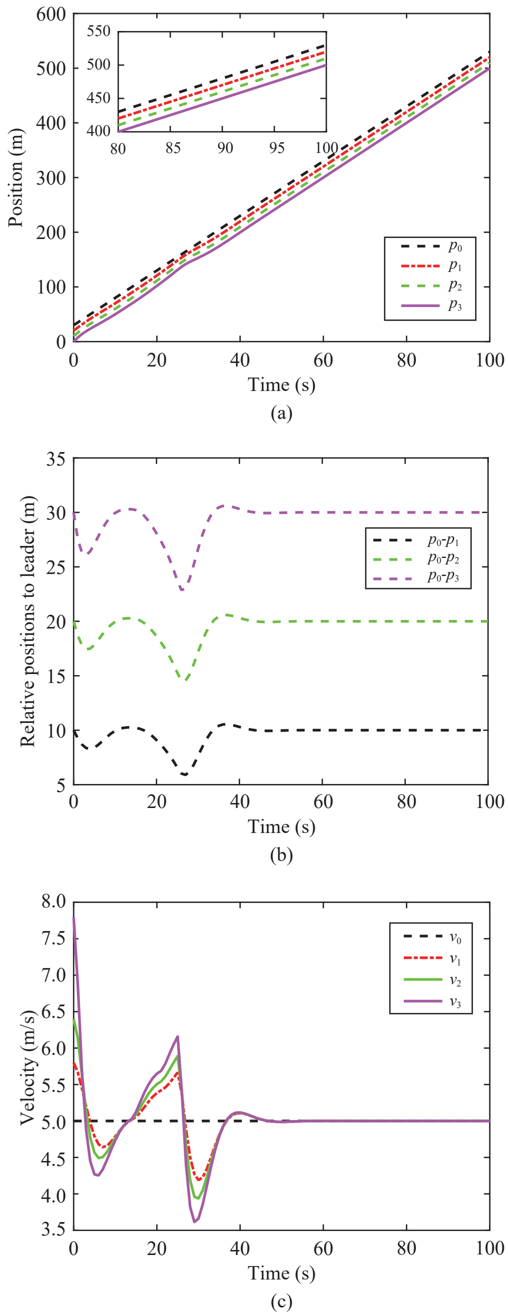


Fig. 2. State trajectories of the closed-loop system: (a) Vehicles' positions; (b) Vehicles' relative positions to the leader; (c) Vehicles' velocities.

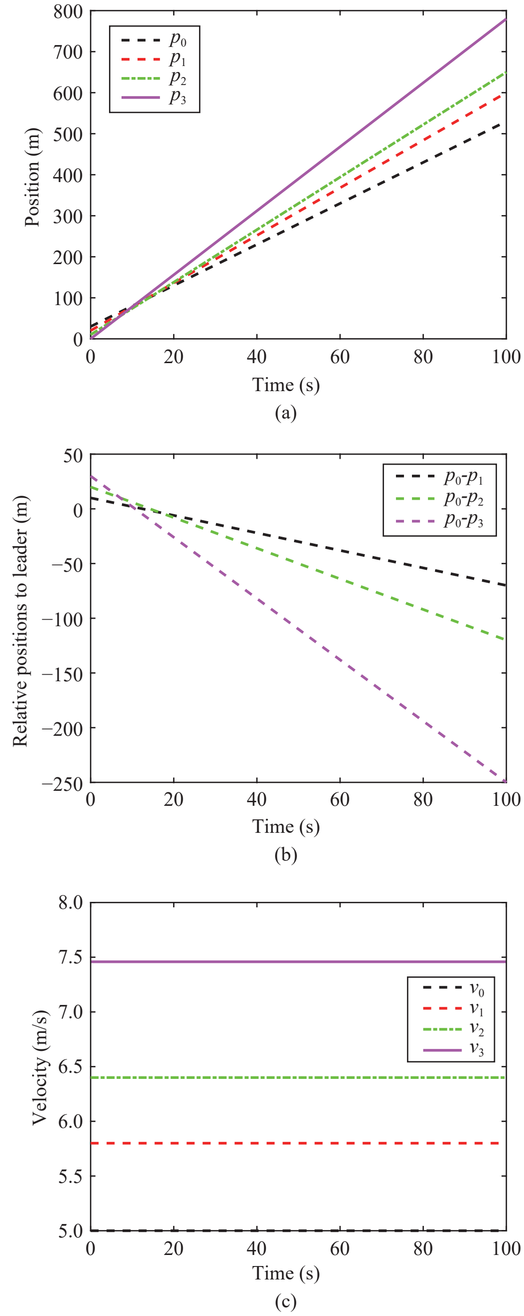
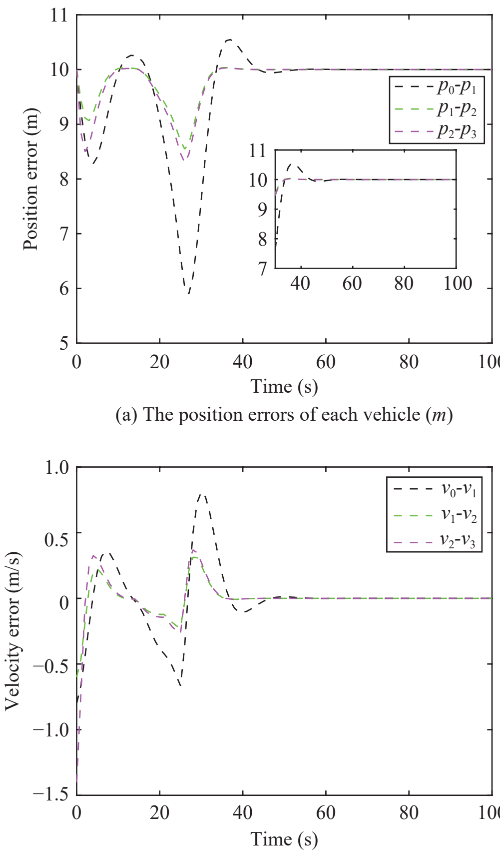


Fig. 3. State trajectories without controllers: (a) Vehicles' positions; (b) Vehicles' relative positions to the leader; (c) Vehicles' velocities.

V. Conclusion

In this paper, we have investigated the PIO-based platooning control for homogeneous connected automated vehicles subject to replay attacks. First, a PIO has been developed to estimate the desired state of vehicles. Then, the closed-loop system based on the PIO has been transformed into a switched and time-delayed one for the convenience of performance analysis and parameter design. In the framework of Lyapunov stability, some sufficient conditions have been derived and the desired controller gains have been formulated via the solu-



(a) The position errors of each vehicle (m)

(b) The velocity error of each vehicle (m/s)

Fig. 4. The error trajectories for vehicle platoon system under the proposed controller.

tions of certain matrix inequalities only dependent on maximum and minimum eigenvalues of communication topologies. Further research topics include the extension of the developed results to other cyber physical systems [44], [45] or further, disclosing the influence of replay attacks.

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