

Observer-Based Periodic Memory-Event-Triggered Tracking Control for Networked Autonomous Vehicles With Deception Attacks and Disturbance

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Abstract—This article addresses the problem of observer-based periodic memory-event-triggered tracking control for networked autonomous vehicles subject to deception attacks and disturbance. By means of sampling output, a new extended state observer is developed to generate estimated signals for vehicles under external disturbances. In order to conserve the network resources, a periodic dynamic memory-event-triggered scheme (DMETS) is put forward, where the estimates are allowed to be transmitted only if the event-triggered condition using historical signals is violated. Based on disturbance estimation and neural network (NN) technique, a robust tracking controller containing historical signals is designed, such that the influence of deception attacks can be considerably attenuated. With the help of the designed periodic memory-event-triggered control strategy, the stability analysis is established to guarantee that the networked autonomous vehicles fulfill desirable disturbance rejection stability. At last, the outcomes of the simulation are verified the superiority of the designed periodic memory-event-triggered control strategy.

Index Terms—Deception attacks, networked autonomous vehicles, memory-event-triggered scheme, disturbance, observer.

I. INTRODUCTION

AUTOMATED vehicles are extensively utilized across various fields such as logistics, autonomous sanitation, and

intelligent transportation due to their ability to reduce fuel consumption, alleviate traffic congestion, and optimize workforce utilization [1], [2], [3]. An essential aspect of controlling automated vehicles is tracking control, which necessitates adjacent vehicles to maintain a specific distance while moving forward in a queue [4]. To ensure the stability and safety of automated vehicles, effective distance strategy and control method are imperative. Common approaches to distance control include maintaining a constant spacing and employing a constant time headway spacing [5]. Within the existing literature, prevalent control techniques encompass backstepping control [6], robust control [7], and fuzzy control [8]. With the evolution of wireless communication technology, automated vehicles have the capability to carry out control tasks by transmitting data remotely via wireless networks. Nonetheless, the tracking control of networked automated vehicles still faces inevitable hurdles, such as limited bandwidth and network security. According to the research above, it is necessary to design a resource-effective tracking control strategy, which can obtain the desirable distance control performance while decreasing the unnecessary communication.

To combat the constraints of limited communication resources, the majority of research aims at event-triggered control (ETC) methods [9], [10], [11], [12], [13], [14]. This control method only requires data transmission when specific triggering conditions are violated, thereby minimizing redundant data transmission. Recently, existing studies mainly focus on periodic ETC [15], static ETC [16] and dynamic ETC [17]. However, studies on memory ETC are rare in the vehicle field [18], [19], [20]. For instance, the issue of adaptive memory ETC is investigated for intelligent vehicle transportation systems in [20]. The author of [21] considers the memory-event-triggered H_∞ filter problem of autonomous surface vehicles. The inclusion of historical transmission data in the design of memory-event-triggered scheme (METS) holds practical significance, as it can mitigate unexpected transmissions resulting from abrupt changes in system states. Compared with the traditional ETC strategies, further study on the METC issue for networked autonomous vehicles deserves more attention, which motivates the work of this article.

In practical scenarios, addressing network attacks and various disturbances becomes imperative for the effective ETC issue of

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automated vehicles, as both of them are common obstacles that significantly impact control performance. On the one hand, due to the necessity of transmitting a large amount of data through communication networks, network attacks are sometimes unavoidable, which can lead to malfunctions or even accidents in automated vehicles [22], [23], [24]. Deception attacks, a prevalent type of network attack, can compromise system stability by tampering with original data integrity through the injection of deceptive signals [25], [26], [27], [28]. By employing neural network (NN) technology, neural network-based controllers can effectively compensate for the effects of deception attacks and approximate the attack signals well [26], [29]. Despite numerous security control methods have been proposed for various networked control systems, only a few works consider the ETC of automated vehicles with network attacks, which is one of the motivations of this article.

Additionally, disturbances in autonomous vehicles are inevitable and severely limit system stability performance. To ensure the stability of the system, several disturbance rejection control methods for dealing with disturbances have been proposed [30]. For example, the authors investigate a comprehensive overview of permanent-magnet synchronous motor drives according to disturbance/uncertainty estimation and attenuation (DUEA) techniques in [31]. In [32], the observer-based fault detection filter and controller coordinated design problems of autonomous surface vehicles are studied, such that the robustness of autonomous surface vehicles with external disturbance can be achieved. In [33], the issue of decentralized ETC is dealt with for large-scale systems with disturbances and input and output delays. For the issue of disturbance rejection control in automated vehicles subject to deception attack, it is a significant challenge to achieve a balance between satisfactory control performance and better transmission rate. Unfortunately, few studies have addressed this issue, which is a primary motivation for the research presented in this article.

Motivated by the above discussions, this article aims to consider the observer-based periodic memory-event-triggered tracking control problem for networked autonomous vehicles under deception attacks and disturbance. The designs of the tracking controller and corresponding control method face two major difficulties: 1) Designing useful extended state observer to estimate the system outputs and external disturbance is filled with difficulties as entire sampling state data is not available; 2) It is full of challenges to compromise between a better disturbance rejection capability and less communication overhead for the design of autonomous vehicle tracking control that is composed of memory-event-triggered terms and an NN-based controller. To sum up, the primary novelties of this article are listed as follows:

- 1) In comparison with [10], [16], [20], the adverse impacts of disturbances and deception attacks are not proactively weakened by the designed ETC approaches, which can decline system performance. With the aid of the techniques of DUEA and NN, the joint design of disturbance rejection tracking controller and periodic dynamic memory-event-triggered scheme (DMETS) not only significantly

improves the transport efficiency, but also can resist the deception attacks and disturbance.

- 2) In contrast to the event-triggered schemes in [2], [6], [11], [15], which utilizes the static thresholds, or the scheme proposed in [10], [16], [17], which utilizes the dynamic threshold, the DMETS presented in this article utilizes adaptive threshold and past triggered packets to dynamically reduce unnecessary data transmission induced by disturbances. Additionally, in comparison with the existing deception attacks models [27], [28], the NN strategy is employed to approximate the unknown attack signals. Compared to the NN law in [26], [29], the proposed NN weight law including historical data is updated at the event-triggered times.
- 3) Unlike the ETC strategies in [2], [6], [10], [16], where the control framework is constructed in continuous-time form, the designed METC framework in this article is based on periodic time form, which contains periodic sampling, discrete-time DMETS and discrete-time robust tracking controller. This discrete-time version not only facilitates digital implementation and improves computational efficiency but also naturally eliminates Zeno behavior, hence it is well-suited for practical applications.

The remainder of this article is arranged as follows: Section II refers to the preliminaries and the autonomous vehicle model. The METC for autonomous vehicles under deception attacks is described in Section III. The law of NN weight and the stability analysis are shown in Section IV. Section V provides illustrative simulations to verify the effectiveness of the proposed METC method and Section VI presents the main conclusions.

Notations: For a matrix Y , Y^T and $Y > 0$ refer to the transpose of Y and the symmetric positive definite. The Frobenius norm is represented by $\|Y\|$; $\lambda_{\min}(Y)$ and $\lambda_{\max}(Y)$ respectively stand for the minimum and maximum eigenvalues of Y .

II. PRELIMINARIES

Consider the dynamics of third-order autonomous vehicle model as follows [36]

$$\begin{cases} \dot{p}(t) = v(t) \\ \dot{v}(t) = a(t) \\ \dot{a}(t) = -\frac{1}{\eta}a(t) + \frac{1}{\eta}(u^F(t) + \omega(t)) \end{cases} \quad (1)$$

where $p(t)$, $v(t)$ and $a(t)$ denote the position, velocity, and acceleration of the vehicle; $u^F(t)$ and $\omega(t)$ refer to the control input under deception attacks to be derived later and the unknown external disturbance; $\eta > 0$ stands for the inertial time parameter in the powertrain.

The control target is to maintain a safe distance between leader and follower vehicles while considerably increasing the communication resource utilization in the presence of deception attacks and external disturbances. The dynamics equation of the leader vehicle's is designed as

$$\begin{cases} \dot{p}_0(t) = v_0(t) \\ \dot{v}_0(t) = a_0(t) \\ \dot{a}_0(t) = -\frac{1}{\eta}a_0(t) \end{cases}$$

where $p_0(t)$ and $v_0(t)$ stand for the position and velocity of the leader vehicle; a_0 represents the acceleration of the leader vehicle. The tracking error of vehicles is expressed as

$$\begin{cases} x_1(t) = p_0(t) - p(t) - \iota - p_d \\ x_2(t) = v_0(t) - v(t) \\ x_3(t) = a_0(t) - a(t) \end{cases}$$

where $x_1(t)$, $x_2(t)$ and $x_3(t)$ refer to the following distance, the velocity error and acceleration error; $p_d = T_v(v(t) - v_0(t)) + d_m$ and d_m denotes a minimum safe distance. T_v and ι represent headway time and the vehicle length.

The spacing error of vehicle model can be expressed as

$$\begin{cases} \dot{x}(t) = Ax(t) + B(u^F(t) + \omega(t)) \\ y(t) = Cx(t) \end{cases} \quad (2)$$

where $x(t) = [x_1(t), x_2(t), x_3(t)]^T \in \mathbb{R}^3$, $C = [1 \ 0 \ 0]$, $A = \begin{bmatrix} 0 & 1 & -T_v \\ 0 & 0 & 1 \\ 0 & 0 & -\frac{1}{\eta} \end{bmatrix}$ and $B = \begin{bmatrix} 0 \\ 0 \\ -\frac{1}{\eta} \end{bmatrix}$. $y(t)$ denotes measured output.

In order to handle unknown disturbance $\omega(t)$, the following exogenous system is constructed as

$$\begin{cases} \dot{d}(t) = Dd(t) \\ \omega(t) = Ed(t) \end{cases} \quad (3)$$

where D and E stand for known matrices; $d(t)$ represents an internal variable and satisfy the following condition.

Assumption 1: For the unknown external disturbance, there exists a bounded constant $\bar{d}$ such that $\|\dot{d}(t)\| \leq \bar{d}$.

Defining $\chi = \text{col}(x, d)$, one can obtain the augmented system as follows

$$\begin{cases} \dot{\chi}(t) = \tilde{A}\chi(t) + \tilde{B}u^F(t) \\ y(t) = \tilde{C}\chi(t) \end{cases} \quad (4)$$

where $\tilde{C} = [C \ 0]$, $\tilde{A} = \begin{bmatrix} A & BE \\ 0 & D \end{bmatrix}$ and $\tilde{B} = \begin{bmatrix} B \\ 0 \end{bmatrix}$.

Remark 1: From the system (3), the unknown external disturbance $\omega(t)$ is a type of time-varying data. In practical applications, it is common to represent external disturbances $\omega(t)$ using system (3) as it can effectively model various signals, including constant, ramp and harmonic components [34].

III. METC USING EXTENDED STATE OBSERVER UNDER DECEPTION ATTACKS

This section develops a sampled-data extended state observer to estimate the unknown external disturbance when just the measured output can be obtained and presents a DMETS. Additionally, a memory-event-triggered disturbance rejection controller is designed to address the vehicle-following control problem and updates at triggered instants via a zero-order holder (ZOH). Since the deception attacks occur in the communication channel between the controller and the actuator (see Fig. 1), the NN technique is designed to deal with the influence of attacks.

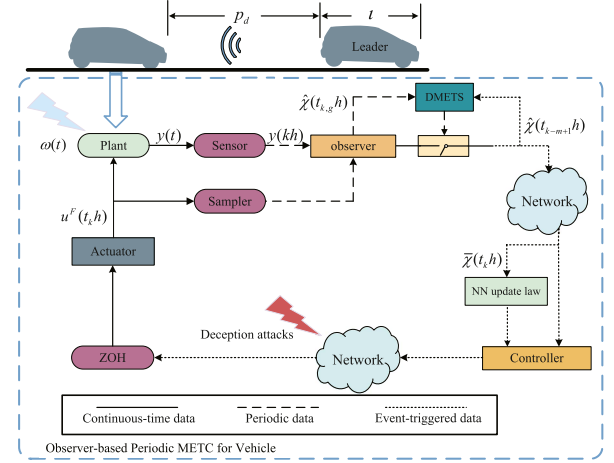


Fig. 1. A framework of observer-based periodic memory-event-triggered tracking control for networked autonomous vehicles subject to deception attacks and disturbance.

A. Extended State Observer Design

For the sake of the following analysis, the k th event-triggered instant is denoted as $t_{k,h}$, where $h > 0$ indicates the sampling period, $k \in \mathbb{N}$ and $t_0 = 0$. $t_{k,g,h} = t_{k,h} + gh$ refers to the current time instant, where $\forall g \in \{1, 2, \dots\}$. By using the measured output, the following extended state observer is proposed for system (4) in the interval $[t_{k,g,h}, t_{k,g+1,h})$

$$\dot{\hat{\chi}}(t) = \tilde{A}\hat{\chi}(t) + \tilde{B}u^F(t) + H(y(t_{k,g,h}) - \tilde{C}\hat{\chi}(t)) \quad (5)$$

where $\hat{\chi}(t) = \text{col}(\hat{x}(t), \hat{d}(t))$, $\hat{x}(t)$ and $\hat{d}(t)$ respectively refer to the estimate of $x(t)$ and $d(t)$; H denotes the observer gain.

Let $z(t) = \chi(t) - \hat{\chi}(t)$ be the estimation error. Combining (4) and (5) yields that

$$\dot{z}(t) = (\tilde{A} - H\tilde{C})z(t) - H(y(t_{k,g,h}) - y(t)) \quad (6)$$

where $t \in [t_{k,g,h}, t_{k,g+1,h})$.

B. DMETS Design

During the data transmission, random fluctuations induced by disturbances are inevitable, which results in the release of more redundant data in memoryless event-triggered schemes. In order to address the aforementioned issue and further utilize the communication resources, the DMETS is designed based on the average of historical observer states to decide whether to transmit information. Denote

$$\mathcal{M}(t, \sigma(t_{k,g,h})) = \sum_{m=1}^{\bar{m}} \|\alpha_m e_m(t)\| - \sigma(t_{k,g,h}) \|\hat{x}(t_{k,g,h})\|, \\ e_m(t) = \hat{\chi}(t_{k,g,h}) - \hat{\chi}(t_{k-m+1,h})$$

where $\sigma(t_{k,g,h})$ and $\bar{m}$ stand for a dynamic threshold to be designed later and the maximum number of historical event-triggered instant; $t_{k-m+1,h}$ represents the past event-triggered instant with $\forall m \in \{1, 2, \dots, \bar{m}\}$; $\alpha_m \in [0, 1]$ refer for the of historical event-triggered instant at time $t_{k-m+1,h}$

and $\sum_{m=1}^{\bar{m}} \alpha_m = 1$; e_m denotes the error between the current sampling instant and the historical event-triggered instant; $\hat{\chi}(t_{k-m+1}h)$ is the past event-triggered data at time $t_{k-m+1}h$. Then, the next triggered instant is generated by the following dynamic memory-event-triggered condition

$$t_{k+1}h = t_k h + \min_{g \geq 1} \{gh \mid \|\mathcal{M}(t, \sigma(t_{k,g}h))\| \geq 0\}. \quad (7)$$

The dynamic threshold σ is changed at each sampling instant, which is determined by the following dynamic law

$$\dot{\sigma}(t) = -\xi_1 \sigma(t) + \frac{\xi_1 \xi_2}{1 + \mathcal{M}(t, \sigma(t_{k,g}h))} \quad (8)$$

where $t \in [t_{k,g}h, t_{k,g+1}h)$, $\xi_1 \geq 0$ and $\xi_2 \geq 0$ and $\sigma(0) = \sigma_0 \geq 0$ denotes the initial condition. By integrating (8) from $t_{k,g}h$ to $t_{k,g+1}h$, the dynamic law can be expressed as

$$\begin{aligned} \sigma(t_{k,g+1}h) &= e^{-\xi_1 h} \sigma(t_{k,g}h) + \int_{t_{k,g}h}^{t_{k,g+1}h} e^{-\xi_1(t_{k,g+1}h-s)} ds \\ &\quad \times \frac{\xi_2 \sigma(t_{k,g}h)}{1 + \mathcal{M}(t, \sigma(t_{k,g}h))} \\ &= e^{-\xi_1 h} \sigma(t_{k,g}h) + \frac{\xi_2 (1 - e^{-\xi_1 h})}{1 + \mathcal{M}(t, \sigma(t_{k,g}h))}. \end{aligned} \quad (9)$$

Remark 2: Unlike other adaptive dynamic METSs [18], [19], the presented DMETS is established in the discrete-time form and relies on the estimates data $\hat{x}(t_{k,g}h)$, making it more applicable to real-world scenarios. Moreover, compared with memoryless schemes [10], [17], [26], the average of historical information $\sum_{m=1}^{\bar{m}} \|\alpha_m e_m(t)\|$ and the corresponding weight α_m are considered in the presented DMETS (7), which facilitates to reduce the unexpected data transmission induced by disturbances. Specifically, by means of historical data, the DMETS (7) prevents redundant triggers that can arise from sudden changes in system output due to disturbances. Note that past data $\hat{\chi}(t_{k-m+1}h)$ is employed in (7) to eliminate unnecessary transmission affected by external factors. $\sum_{m=1}^{\bar{m}} \|\alpha_m e_m(t)\|$ is used to improve the triggered numbers at the crest or trough responses [35].

Remark 3: For (7), the greater the weight α_m , the closer the corresponding event-triggered data is to the current time and vice versa, i.e., $\alpha_1 > \alpha_2 > \dots > \alpha_m$ with $\sum_{m=1}^{\bar{m}} \alpha_m = 1$. This ensures that data closer to the current time have a greater influence on the triggering decision. It is worth noting that considering excessive historical event-triggered data in the design can reduce the utilization rate of storage resources and the sensitivity of the system output. To balance these effects, the maximum number of historical event-triggered data is set as $\bar{m} = 3$. Furthermore, when $\bar{m} = 1$, the DMETS (7) reduces to the traditional dynamic event-triggered scheme.

Lemma 1: [37] Under the dynamic law (8), if two parameters ξ_1 and ξ_2 are selected to satisfy $\xi_1, \xi_2 \geq 0$, ensuring that $\sigma(t) \geq 0$ remains bounded with $\sigma_0 \geq 0$ over time interval $t \in [0, \infty)$. Then, for $\xi_1 > 0$, it follows that $0 \leq \sigma(t_{k,g}h) \leq \sigma_{\max}$, where $\sigma_{\max} = \max\{\sigma_0, \frac{\xi_2}{1-e^{-\xi_1 h}}\}$.

Remark 4: For (8), the threshold σ takes a smaller value and the likelihood of satisfying the condition of DMETS (7)

increases as the error e_m takes greater. When $\xi_1 = 0$ and $\sigma_0 > 0$, the DMETS (7) can be simplified into the event-triggered scheme [9] with fixed threshold. Additionally, when $\xi_1 = 0$ and $\sigma_0 = 0$, the DMETS (7) degrades into the traditional time-triggered scheme. Choosing a smaller value for ξ_1 or a larger value for ξ_2 can cause a more rapid decline of the threshold σ . Therefore, the DMETS (7) can increase the utilization ratio of the resources and network transmission speed.

C. Controller Under Deception Attacks

Taking into account the deception attacks that could impact the information exchange in the controller-to-actuator channel, a NN algorithm is presented to estimate the actual attack signals. Different from the deception attacks modeled in [25], [27], [28], where the deceptive information caused by attacker is estimated by a bounded function. This article proposes a state-dependent deception attacks model with unknown upper bounds, which is more suitable to the actual situation. The memory-event-triggered disturbance rejection controller under deception attacks is formulated by

$$u^F(t) = u(t) + g(\bar{\chi}(t_k h)) \quad (10)$$

$$u(t) = \tilde{u}(t_k h) - \hat{g}(\bar{\chi}(t_k h)) \quad (11)$$

where $\bar{\chi}(t_k h)$ is denoted as $\bar{\chi}(t_k h) = \sum_{m=1}^{\bar{m}} \hat{\chi}(t_{k-m+1}h)$. The unknown nonlinear term $g(\bar{\chi}(t_k h))$ and $\tilde{u}(t_k h)$ refer to the false information affected by the attackers and the control input without deception attacks. $\hat{g}(\bar{\chi}(t_k h))$ denotes the estimation of $g(\bar{\chi}(t_k h))$. Based on the universal approximation property [38] of NN, the nonlinear fraudulent information $g(\bar{\chi}(t_k h))$ can be approximated in a compact $\Omega \subset \mathbb{R}^4$ for $\forall \bar{\chi}(t_k h) \in \Omega$. Note that by randomly choosing the weight $\bar{v} \in \mathbb{R}^{4 \times j}$ of the input-to-hidden layer, the basis function $S(\bar{v}^T \bar{\chi}(t_k h))$ forms a basis and the NN approximation property remains valid. The following single-hidden layer feedback NN, designed in discrete form [38], is formulated under event-triggered interval

$$g(\bar{\chi}(t_k h)) = W^{*T} S(\bar{v}^T \bar{\chi}(t_k h)) + \epsilon(\bar{\chi}(t_k h)) \quad (12)$$

where $W^* \in \mathbb{R}^j$ refers to the weight for hidden-to-output layer that contains j NN nodes. $\epsilon(\bar{\chi}(t_k h))$ implies the NN approximation error.

Assumption 2: The weight W^* , basis function S and NN error ϵ are bounded, that is, there exist three positive constants $W_{\max}^*$, $S_{\max}$ and $\epsilon_{\max}$ such that $\|W^*\| \leq W_{\max}^*$, $\|S\| \leq S_{\max}$ and $\|\epsilon\| \leq \epsilon_{\max}$.

The estimate of $g(\bar{\chi}(t_k h))$ is described by

$$\hat{g}(\bar{\chi}(t_k h)) = \hat{W}_F^T(t) S(\bar{v}^T \bar{\chi}(t_k h)) \quad (13)$$

where $\hat{W}_F(t) \in \mathbb{R}^j$ implies the estimated NN weight changed at time $t_k h$.

With observer (5) in mind, the control input without deception attacks in (11) is defined as follows

$$\tilde{u}(t_k h) = \sum_{m=1}^{\bar{m}} \left(K \hat{x}(t_{k-m+1}h) - E \hat{d}(t_{k-m+1}h) \right) \quad (14)$$

where $t \in [t_k h, t_{k+1} h)$, K refers to the controller gain to be designed later.

By the DMETS (7) and (14), the memory-event-triggered disturbance rejection controller is determined by

$$u^F(t) = \sum_{m=1}^{\bar{m}} \left(K \hat{x}(t_{k,g} h) - E \hat{d}(t_{k,g} h) - \tilde{K} e_m(t) - \hat{g}(\bar{\chi}(t_k h)) + g(\bar{\chi}(t_k h)) \right) \quad (15)$$

where $t \in [t_k h, t_{k+1} h)$ and $\tilde{K} = [K, -E]$.

Remark 5: In the traditional control method without using the NN technique and disturbance estimation [25], [27], [28], the results are often conservative as the adverse effect of disturbances can not be effectively mitigated. It is worth noting that these methods are typically applicable only in scenarios where the upper bounds of deception attacks are known. The proposed memory-event-triggered disturbance rejection controller (15) is based on the NN technique and disturbance estimation, such that the ideal disturbance rejection ability can be maintained and the effect of deception attacks can be effectively compensated.

For simplifying analysis, let

$$\begin{aligned} \vartheta_1(t) &= z(t) - z(t_{k,g} h), \\ \vartheta_2(t) &= \chi(t) - \chi(t_{k,g} h), \vartheta_3(t) = y(t_{k,g} h) - y(t), \\ \vartheta_4(t) &= \tilde{W}_F^T(t_k h) S(\bar{v}^T \bar{\chi}(t_k h)) + \epsilon(\bar{\chi}(t_k h)) \end{aligned}$$

where $t \in [t_k h, t_{k+1} h)$, $\tilde{W}_F(t_k h) = \hat{W}_F(t_k h) - W^*$ refers to the weight matrix estimate error.

Define $\Upsilon(t) = \text{col}(x(t), z(t))$. Combining (2), (6) and (15), one can get

$$\begin{aligned} \dot{\Upsilon}(t) &= \Gamma_1 \Upsilon(t) + \Gamma_2 \left(\vartheta_1(t) - \vartheta_2(t) - \sum_{m=1}^{\bar{m}} e_m(t) \right) - \Gamma_3 \vartheta_3(t) \\ &\quad + \Gamma_4 \vartheta_4(t), t \in [t_k h, t_{k+1} h) \end{aligned} \quad (16)$$

$$\text{where } \Gamma_1 = \begin{bmatrix} A + BK & -B\tilde{K} \\ 0 & \tilde{A} - H\tilde{C} \end{bmatrix}, \quad \Gamma_2 = \begin{bmatrix} B\tilde{K} \\ 0 \end{bmatrix}, \quad \Gamma_3 = \begin{bmatrix} 0 \\ H\tilde{C} \end{bmatrix}, \quad \Gamma_4 = \begin{bmatrix} -B \\ 0 \end{bmatrix}.$$

Remark 6: Compared with the works [6], [20] where the control designs are investigated based on the backstepping or linear matrix inequality technique, a new DMETS under the periodic control framework is developed for networked autonomous systems with deception attacks. Different from the traditional control strategies [2], [6], [10], [16], where the controllers are updated continuously. This article proposes the periodic METC method, where measurement and estimation of autonomous vehicle and controller design are in periodic sampling instants rather than continuous instants. Such a situation of periodic METC is easy to implement and helps to mitigate the pressure of network burden.

IV. MAIN RESULTS

In this section, the observer-based periodic METC is investigated to guarantee the stability of dynamics (16) under

deception attacks. First, the following analysis is developed to present the adaptive law of NN weight. Different from other NN methods [26], [29], the law of NN weight is adapted using historical information, which allows for a better approximation of deception attack signals. The law of NN weight is determined by

$$\begin{aligned} \hat{W}_F(t) &= \hat{W}_F(t_{k+1} h) - \varrho_1 \frac{S(\bar{v}^T \bar{\chi}(t_k h)) z_1(t_k h)}{1 + \|z_1(t_k h)\|^2} \\ &\quad - \varrho_2 \hat{W}_F(t_{k+1} h), t = t_{k+1} h \end{aligned} \quad (17)$$

where $\varrho_1 > 0$ and $\varrho_2 > 0$ represent the learning rate and the sigma modification term [39].

With (17) in mind, the weight estimation error is formulated as follows

$$\begin{aligned} \tilde{W}_F(t) &= \hat{W}_F(t) - W^* = \tilde{W}_F(t_{k+1} h) - \varrho_2 \hat{W}_F(t_{k+1} h) \\ &\quad - \varrho_1 \frac{S(\bar{v}^T \psi(t_k h)) z_1(t_k h)}{1 + \|z_1(t_k h)\|^2}, t = t_{k+1} h. \end{aligned} \quad (18)$$

Remark 7: From (17), choosing appropriate initial values $\hat{W}_F(0)$, $\bar{v}(0)$ and learning rates ϱ_1 , ϱ_2 can improve the learning speed and accuracy of the NN weight update rule. In addition, a smaller sampling period h can achieve better approximation accuracy of NN weight by increasing data transmission. However, this comes at the cost of longer computation time and limited control performance. Therefore, there is a trade-off between conserving bandwidth resources and achieving satisfactory NN approximation performance.

Note that the NN method is employed to approximate the deception data $g(\bar{\chi}(t_k h))$ and the weight estimation error in (18) is tuned only at the triggered instant $t_k h$. In order to ensure the accuracy of NN, we give the following lemma to present the boundedness of the estimated NN weight.

Lemma 2: Under the law (17) of NN weight and Assumption 2. If two parameters ϱ_1 and ϱ_2 are chosen to satisfy $\varrho_1 > 0$ and $\varrho_2 < \frac{1}{2}$ such that the $\tilde{W}_F(t)$ is bounded over time interval $t \in [0, \infty)$.

Proof: Formulate the Lyapunov function for NN weight estimation error (18) as follows $V_1(W_F) = \tilde{W}_F^T(t_{k+1}^- h) \tilde{W}_F(t_{k+1}^- h)$. It is noteworthy that $\tilde{W}_F(t)$ only updates at the event-triggered instant $t = t_{k+1} h$. Therefore, one acquires $\dot{\tilde{W}}_F(t) = 0$, $t \in [t_k h, t_{k+1} h)$, then $\dot{V}(\tilde{W}_F) = 0$ holds.

From (18), the jumping of ΔV_1 can be transformed as

$$\begin{aligned} \Delta V_1(\tilde{W}_F) &= \tilde{W}_F^T(t) \tilde{W}_F(t) - \tilde{W}_F^T(t_{k+1}^- h) \tilde{W}_F(t_{k+1}^- h) \\ &= \varrho_2^2 \hat{W}_F^T(t_{k+1}^- h) \hat{W}_F(t_{k+1}^- h) - 2\varrho_2 \tilde{W}_F^T(t_{k+1}^- h) \hat{W}_F(t_{k+1}^- h) \\ &\quad + \varrho_1^2 \kappa^T(t_k h) \kappa(t_k h) z_1^2(t_k h) - 2\varrho_1 \tilde{W}_F^T(t_{k+1}^- h) \kappa(t_k h) \\ &\quad \times z_1(t_k h) + 2\varrho_1 \varrho_2 \hat{W}_F^T(t_{k+1}^- h) \kappa(t_k h) z_1(t_k h) \end{aligned} \quad (19)$$

where $\kappa(t_k h) = \frac{S(\bar{v}^T \bar{\chi}(t_k h))}{1 + \|z_1(t_k h)\|^2}$.

It follows from (18) that $\hat{W}_F(t_{k+1}^-h) = W^* + \tilde{W}_F(t_{k+1}^-h)$, equation (19) can be further derived as

$$\begin{aligned} \Delta V_1(\tilde{W}_F) &\leq \varrho_2^2 \tilde{W}_F^T(t_{k+1}^-h) \tilde{W}_F(t_{k+1}^-h) + 2\varrho_2^2 \tilde{W}_F^T(t_{k+1}^-h) W^* \\ &\quad + \varrho_2^2 W^{*T} W^* + \varrho_1^2 \kappa^T(t_k h) \kappa(t_k h) z_1^2(t_k h) \\ &\quad - 2\varrho_1 \tilde{W}_F^T(t_{k+1}^-h) \kappa(t_k h) z_1(t_k h) - 2\varrho_2 \\ &\quad \times \tilde{W}_F^T(t_{k+1}^-h) \tilde{W}_F(t_{k+1}^-h) - 2\varrho_2 \tilde{W}_F^T(t_{k+1}^-h) W^* \\ &\quad + 2\varrho_1 \varrho_2 \tilde{W}_F^T(t_{k+1}^-h) \kappa(t_k h) z_1(t_k h) \\ &\quad + 2\varrho_1 \varrho_2 W^{*T} \kappa(t_k h) z_1(t_k h), t = t_{k+1} h. \end{aligned} \quad (20)$$

According to Young's inequality and Assumption 2, it is clear that $0 \leq \frac{\|z_1(t_k h)\|}{1 + \|z_1(t_k h)\|^2} < 1$. The following inequality can be established by (20)

$$\Delta V_1(\tilde{W}_F) \leq -\bar{\varrho}_1 \|\tilde{W}_F(t_{k+1}^-h)\|^2 + \bar{\varrho}_2 \|\tilde{W}_F(t_{k+1}^-h)\| + \bar{\varrho}_3 \quad (21)$$

where $\bar{\varrho}_1 = \varrho_2 - 2\varrho_2^2$, $\bar{\varrho}_2 = 2\varrho_1(\varrho_2 - 1)S_M$, $\bar{\varrho}_3 = (\varrho_2 + 2\varrho_2^2)\|W_{\max}^*\|^2 + 2\varrho_1\varrho_2 S_{\max}\|W_{\max}^*\| + \varrho_1^2 S_{\max}^2$. The parameter ϱ_2 is reasonably designed to satisfy $\varrho_2 < \frac{1}{2}$. Then, it follows that $\bar{\varrho}_1 > 0$, and (21) can be written as

$$\begin{aligned} \Delta V_1(\tilde{W}_F) &\leq -\bar{\varrho}_4 - \frac{\bar{\varrho}_1}{2} \|\tilde{W}_F(t_{k+1}^-h)\|^2 + \hat{\varrho} \\ &\leq -\frac{\bar{\varrho}_1}{2} \|\tilde{W}_F(t_{k+1}^-h)\|^2 + \hat{\varrho} \end{aligned} \quad (22)$$

where $\bar{\varrho}_4 = \sqrt{\frac{\bar{\varrho}_1}{2}} \|\tilde{W}_F(t_{k+1}^-h)\| - \frac{\bar{\varrho}_2}{\sqrt{2\bar{\varrho}_1}}$, $\hat{\varrho} = \frac{\bar{\varrho}_2^2}{2\bar{\varrho}_1} + \bar{\varrho}_3$.

From (22), one knows that if $\|\tilde{W}_F(t_{k+1}^-h)\|^2 > \frac{2\hat{\varrho}}{\bar{\varrho}_1}$ holds, then $\Delta V_1(\tilde{W}_F) < 0$ can be guaranteed. Hence, the estimated weight error $\tilde{W}_F(t)$ can achieve a bounded performance. ■

Next, based on Lemma 2, the following theorem is given to guarantee the stability analysis of system (16) with deception attacks and disturbance.

Theorem 1: For the autonomous vehicle (16) with the law of NN weight (17) and DMETS (7). Under Assumptions 1-2, if controller gain K and observer gain H are chosen such that $A + HK$ and $\hat{A} + H\hat{C}$ can be the Hurwitz matrix, and there exists symmetric matrix $P = P^T > 0$ satisfying $\Gamma_1^T P + P\Gamma_1 = -\beta I$ with $\beta > 0$, then the states of autonomous vehicle (16) are bounded, when the following conditions hold

$$\bar{\delta}_2 < 1, 0 < \beta_0 < \bar{\beta} \quad (23)$$

where $\delta_1 = \frac{\|P\Gamma_2\|}{(\bar{\beta} - \beta_0)\lambda_{\min}(P)}$, $\delta_2 = \frac{\|P\Gamma_3\|}{(\bar{\beta} - \beta_0)\lambda_{\min}(P)}$,

$$\delta_3 = \frac{\|P\Gamma_4\|}{(\bar{\beta} - \beta_0)\lambda_{\min}(P)}, \delta_4 = \|A\| + \|HC\| + \|H\|,$$

$$\delta_5 = \|A\| + \|B\tilde{K}\| + \|B\|, \bar{\beta} = \beta/2\lambda_{\min}(P),$$

$$\begin{aligned} \bar{\delta}_2 &= \delta_1 \delta_4 h e^{\beta_0 h} + 2\bar{m} \delta_1 \sigma_{\max} e^{\beta_0 h} + (\delta_1 + \delta_2 \|C\| \\ &\quad + \delta_1 \delta_4 h \|C\| e^{\beta_0 h}) (3\delta_5 h e^{\beta_0 h} + 2\bar{m} \delta_5 \sigma_{\max} h e^{\beta_0 h}), \end{aligned}$$

$$\begin{aligned} \bar{\delta}_3 &= \left(\frac{2\hat{\varrho} S_{\max}}{\bar{\varrho}_1} + \epsilon_{\max} \right) (\delta_1 \delta_5 h e^{\beta_0 h} + \delta_3 + \delta_2 \delta_5 \|C\| h e^{\beta_0 h} \\ &\quad + \delta_1 \delta_4 \delta_5 \|C\| h^2 e^{2\beta_0 h}) + \delta_1 (\tilde{d}h + \delta_5 \tilde{d}h^2). \end{aligned}$$

Proof: Formulate the Lyapunov functional as follows: $V(t) = \Upsilon^T(t)P\Upsilon(t) + V_1(W_F(t_{k+1}^-h))$, $t \in [t_k h, t_{k+1} h)$. With the help of Lemma 2, the estimated NN weight error $\tilde{W}_F$ can be adaptively regulated only at each triggering instant. Therefore, the stability analysis consists of two parts: the proof in $[t_k h, t_{k+1} h)$ and the jump dynamics at the transmission instant $t_{k+1} h$.

Step 1: the proof in $[t_k h, t_{k+1} h)$:

From (18), the estimated NN weight error $\tilde{W}_F$ stays the same during $[t_k h, t_{k+1} h)$, namely, $\tilde{W}_F^T(t_{k+1}^-h) \tilde{W}_F(t_{k+1}^-h) = 0$. Taking the time derivative of $V(t)$ along the system (16), one gets

$$\begin{aligned} \dot{V}(t) &= -\beta \|\Upsilon(t)\|^2 + 2\Upsilon^T(t)P\Gamma_2 \left(\vartheta_1(t) - \sum_{m=1}^{\bar{m}} e_m(t) \right. \\ &\quad \left. - \vartheta_2(t) \right) + 2\Upsilon^T(t)P\Gamma_3 \vartheta_3(t) + 2\Upsilon^T(t)P\Gamma_4 \vartheta_4(t) \\ &\leq -\frac{\beta}{\lambda_{\max}(P)} V(t) + \frac{2\|P\Gamma_2\|}{\sqrt{\lambda_{\min}(P)}} \sqrt{V(t)} \left(\|\vartheta_1(t)\| \right. \\ &\quad \left. + \sum_{m=1}^{\bar{m}} \|e_m(t)\| + \|\vartheta_2(t)\| \right) + \frac{2\|P\Gamma_3\|}{\sqrt{\lambda_{\min}(P)}} \sqrt{V(t)} \\ &\quad \times \|\vartheta_3(t)\| + \frac{2\|P\Gamma_4\|}{\sqrt{\lambda_{\min}(P)}} \sqrt{V(t)} \|\vartheta_4(t)\|. \end{aligned} \quad (24)$$

From (24), it yields that

$$\begin{aligned} \sqrt{\dot{V}(t)} &\leq -\bar{\beta} \sqrt{V(t)} + \frac{\|P\Gamma_2\|}{\sqrt{\lambda_{\min}(P)}} \left(\|\vartheta_1(t)\| \right. \\ &\quad \left. + \sum_{m=1}^{\bar{m}} \|e_m(t)\| + \|\vartheta_2(t)\| \right) + \frac{\|P\Gamma_3\|}{\sqrt{\lambda_{\min}(P)}} \|\vartheta_3(t)\| \\ &\quad + \frac{\|P\Gamma_4\|}{\lambda_{\min}(P)} \|\vartheta_4(t)\| \end{aligned} \quad (25)$$

where $\bar{\beta}$ is defined in Theorem 1.

Integrating (25), one obtains

$$\begin{aligned} \sqrt{V(t)} &\leq e^{-\bar{\beta}t} \sqrt{V(0)} + \frac{\|P\Gamma_2\|}{\sqrt{\lambda_{\min}(P)}} \int_0^t e^{-\bar{\beta}(t-s)} \left(\|\vartheta_1(s)\| \right. \\ &\quad \left. + \sum_{m=1}^{\bar{m}} \|e_m(s)\| + \|\vartheta_2(s)\| \right) ds + \frac{\|P\Gamma_3\|}{\sqrt{\lambda_{\min}(P)}} \\ &\quad \times \int_0^t e^{-\bar{\beta}(t-s)} (\|\vartheta_3(s)\| + \|\vartheta_4(s)\|) ds. \end{aligned} \quad (26)$$

Defining $0 < \beta_0 < \bar{\beta}$ and multiplying both sides of (26) by $e^{\beta_0 t}$, one can yield

$$\begin{aligned} e^{\beta_0 t} \sqrt{V(t)} &\leq e^{-(\bar{\beta} - \beta_0)t} \sqrt{V(0)} + \delta_1 \sup_{0 \leq s \leq t} \left[e^{\beta_0 s} \left(\|\vartheta_1(s)\| \right. \right. \\ &\quad \left. \left. + \sum_{m=1}^{\bar{m}} \|e_m(s)\| + \|\vartheta_2(s)\| \right) \right] + \delta_2 \sup_{0 \leq s \leq t} \\ &\quad (e^{\beta_0 s} \|\vartheta_3(s)\|) + \delta_3 \sup_{0 \leq s \leq t} (e^{\beta_0 s} \|\vartheta_4(s)\|) \end{aligned} \quad (27)$$

where δ_1 , δ_2 and δ_3 are defined in Theorem 1.

Because $\bar{\beta} - \beta_0 > 0$, (27) can be further calculated as

$$\begin{aligned} \sup_{0 \leq s \leq t} (e^{\beta_0 s} \|\Upsilon(s)\|) &\leq \frac{\sqrt{V(0)}}{\sqrt{\lambda_{\min}(P)}} + \delta_1 \sup_{0 \leq s \leq t} \\ &\times \left[e^{\beta_0 s} \left(\|\vartheta_1(s)\| + \sum_{m=1}^{\bar{m}} \|e_m(s)\| + \|\vartheta_2(s)\| \right) \right] \\ &+ \delta_2 \sup_{0 \leq s \leq t} (e^{\beta_0 s} \|\vartheta_3(s)\|) + \delta_3 \sup_{0 \leq s \leq t} (e^{\beta_0 s} \|\vartheta_4(s)\|). \end{aligned} \quad (28)$$

In order to estimate $\sup_{0 \leq s \leq t} (e^{\beta_0 s} \|\vartheta_1(s)\|)$, it follows from (6) that for $t \in [t_{k,g}h, t_{k,g+1}h)$

$$\|\dot{z}(t)\| \leq \delta_4 (\|\Upsilon(t)\| + \|\vartheta_3(t)\|) \quad (29)$$

where $\delta_4 = \|A\| + \|HC\| + \|H\|$.

Recalling $\vartheta_1(t) = z(t) - z(t_{k,g}h)$, $t \in [t_{k,g}h, t_{k,g+1}h)$, inequality (29) can be expressed as

$$\begin{aligned} e^{\beta_0 t} \|\vartheta_1(t)\| &\leq \delta_4 e^{\beta_0 t} \int_{t_{k,g}h}^t (\|\Upsilon(s)\| + \|\vartheta_3(s)\|) ds \\ &\leq \delta_4 h e^{\beta_0 t} \sup_{t_{k,g}h \leq s \leq t} (\|\Upsilon(s)\| + \|\vartheta_3(s)\|) \\ &\leq \delta_4 h e^{\beta_0 h} \sup_{t_{k,g}h \leq s \leq t} e^{\beta_0 s} (\|\Upsilon(s)\| + \|\vartheta_3(s)\|). \end{aligned} \quad (30)$$

With (30) in mind, one can get

$$\begin{aligned} \sup_{0 \leq s \leq t} (e^{\beta_0 s} \|\vartheta_1(s)\|) &\leq \delta_4 h e^{\beta_0 h} \sup_{0 \leq s \leq t} (e^{\beta_0 s} \|\Upsilon(s)\|) \\ &+ \delta_4 h e^{\beta_0 h} \sup_{0 \leq s \leq t} (e^{\beta_0 s} \|\vartheta_3(s)\|). \end{aligned} \quad (31)$$

Next, to estimate $\sup_{0 \leq s \leq t} (e^{\beta_0 s} \sum_{m=1}^{\bar{m}} \|e_m(s)\|)$, the term $\sum_{m=1}^{\bar{m}} \|e_m(s)\|$ in DMETS (7) can be handled as $\sum_{m=1}^{\bar{m}} \|e_m(s)\| = \sum_{m=1}^{\bar{m}} \|\hat{\chi}(t_{k,g}h) - \hat{\chi}(t_{k-m+1}h)\| \leq \bar{m} \sigma_{\max} \|\hat{x}(t_{k,g}h)\| \leq \bar{m} \sigma_{\max} (\|z(t_{k,g}h)\| + \|x(t_{k,g}h)\|)$. For $t \in [t_{k,g}h, t_{k,g+1}h)$, the following inequality is established

$$\begin{aligned} &\sup_{t_{k,g}h \leq s \leq t} \left(e^{\beta_0 s} \sum_{m=1}^{\bar{m}} \|e_m(s)\| \right) \\ &\leq \bar{m} \sigma_{\max} \sup_{t_{k,g}h \leq s \leq t} [e^{\beta_0 s} (\|z(t_{k,g}h)\| + \|x(t_{k,g}h)\|)] \\ &\leq \bar{m} \sigma_{\max} e^{\beta_0 h} \sup_{t_{k,g}h \leq s \leq t} [e^{\beta_0 s} (\|z(s)\| + \|x(s)\|)] \\ &\leq 2\bar{m} \sigma_{\max} e^{\beta_0 h} \sup_{t_{k,g}h \leq s \leq t} (e^{\beta_0 s} \|\Upsilon(s)\|). \end{aligned} \quad (32)$$

In particular, (32) over $[t_{k,g}h, t_{k,g+1}h)$ can be generalized into $[0, t)$, one arrives at

$$\begin{aligned} &\sup_{0 \leq s \leq t} \left(e^{\beta_0 s} \sum_{m=1}^{\bar{m}} \|e_m(s)\| \right) \\ &\leq 2\bar{m} \sigma_{\max} e^{\beta_0 h} \sup_{0 \leq s \leq t} (e^{\beta_0 s} \|\Upsilon(s)\|). \end{aligned} \quad (33)$$

Then, to estimate $\sup_{0 \leq s \leq t} (e^{\beta_0 s} \|\vartheta_2(s)\|)$, it can be obtained from (2) and (15) that

$$\begin{aligned} \dot{x}(t) &= Ax(t) - \sum_{m=1}^{\bar{m}} B\tilde{K}e_m(t) + BKx(t_{k,g}h) \\ &- B\tilde{K}z(t_{k,g}h) + BE(d(t) - d(t_{k,g}h)) - B\vartheta_4(t). \end{aligned} \quad (34)$$

Based on Assumption 1, it is derived that $\|d(t) - d(t_{k,g}h)\| \leq \tilde{d}h$ $t \in [t_{k,g}h, t_{k,g+1}h)$. From (34), one has

$$\begin{aligned} \|\dot{x}(t)\| &\leq \delta_5 (\|\Upsilon(t)\| + \|z(t_{k,g}h)\| + \|x(t_{k,g}h)\|) \\ &+ \delta_5 (\tilde{d}h + \sum_{m=1}^{\bar{m}} \|e_m(t)\| + \|\vartheta_4(t)\|) \end{aligned} \quad (35)$$

where $\delta_5 = \|A\| + \|B\tilde{K}\| + \|B\|$.

Bearing $\vartheta_2(t) = \chi(t) - \chi(t_{k,g}h)$, $t \in [t_{k,g}h, t_{k,g+1}h)$ in mind, one obtains $\|\vartheta_2(t)\| \leq \tilde{d}h + \|x(t) - x(t_{k,g}h)\|$. By (35), it yields that

$$\begin{aligned} e^{\beta_0 t} \|\vartheta_2(t)\| &\leq \tilde{d}h e^{\beta_0 t} + e^{\beta_0 t} \int_{t_{k,g}h}^t \|\dot{x}(s)\| ds \\ &\leq (1 + \delta_5 h) \tilde{d}h e^{\beta_0 t} + \delta_5 h e^{\beta_0 t} \left[\sup_{t_{k,g}h \leq s \leq t} (\|x(t_{k,g}h)\| + \|\Upsilon(s)\| \right. \\ &\quad \left. + \|z(t_{k,g}h)\|) + \sup_{t_{k,g}h \leq s \leq t} \left(\sum_{m=1}^{\bar{m}} \|e_m(s)\| + \|\vartheta_4(s)\| \right) \right] \\ &\leq (1 + \delta_5 h) \tilde{d}h e^{\beta_0 t} + 3\delta_5 h e^{\beta_0 h} \sup_{t_{k,g}h \leq s \leq t} (e^{\beta_0 s} \|\Upsilon(s)\|) \\ &\quad + \delta_5 h e^{\beta_0 h} \sup_{t_{k,g}h \leq s \leq t} \left[e^{\beta_0 s} \left(\sum_{m=1}^{\bar{m}} \|e_m(s)\| + \|\vartheta_4(s)\| \right) \right]. \end{aligned} \quad (36)$$

Substituting (33) into (36), it holds that

$$\begin{aligned} \sup_{0 \leq s \leq t} (e^{\beta_0 s} \|\vartheta_2(s)\|) &\leq (\tilde{d}h + \delta_5 \tilde{d}h^2) e^{\beta_0 t} + (3\delta_5 h e^{\beta_0 h} \\ &\quad + 2\bar{m} \sigma_{\max} \delta_5 h e^{2\beta_0 h}) \sup_{0 \leq s \leq t} (e^{\beta_0 s} \|\Upsilon(s)\|) \\ &\quad + \delta_5 h e^{\beta_0 h} \sup_{0 \leq s \leq t} (e^{\beta_0 s} \|\vartheta_4(s)\|). \end{aligned} \quad (37)$$

Following $\vartheta_3(t) = y(t_{k,g}h) - y(t) = C(x(t_{k,g}h) - x(t))$, it can be shown from (36) that

$$\begin{aligned} e^{\beta_0 t} \|\vartheta_3(t)\| &\leq e^{\beta_0 t} \int_{t_{k,g}h}^t \|C\dot{x}(s)\| ds \\ &\leq 3\delta_5 \|C\| h e^{\beta_0 h} \sup_{t_{k,g}h \leq s \leq t} (e^{\beta_0 s} \|\Upsilon(s)\|) + \delta_5 h e^{\beta_0 h} \|C\| \\ &\quad \times \sup_{t_{k,g}h \leq s \leq t} \left[e^{\beta_0 s} \left(\sum_{m=1}^{\bar{m}} \|e_m(s)\| + \|\vartheta_4(s)\| \right) \right]. \end{aligned} \quad (38)$$

Together with (37) and (38) results in

$$\begin{aligned} \sup_{0 \leq s \leq t} (e^{\beta_0 s} \|\vartheta_3(s)\|) &\leq \delta_5 \|C\| h e^{\beta_0 h} \sup_{0 \leq s \leq t} (e^{\beta_0 s} \|\vartheta_4(s)\|) \\ &+ (3\delta_5 h e^{\beta_0 h} \|C\| + 2\bar{m}\sigma_{\max} \delta_5 \|C\| h e^{2\beta_0 h}) \\ &\times \sup_{0 \leq s \leq t} (e^{\beta_0 s} \|\Upsilon(s)\|). \end{aligned} \quad (39)$$

By means of Assumption 2 and Lemma 2, one has that $\vartheta_4(t) = \tilde{W}_F^T(t_k h) S(\bar{v}^T \bar{\chi}(t_k h)) + \epsilon(\bar{\chi}(t_k h))$ is bounded because $\tilde{W}_F$ is bounded and converges to $\frac{2\hat{\rho}}{\bar{\rho}_1}$. In order to estimate $\sup_{0 \leq s \leq t} (e^{\beta_0 s} \|\vartheta_4(s)\|)$, one acquires

$$\sup_{0 \leq s \leq t} (e^{\beta_0 s} \|\vartheta_4(s)\|) \leq e^{\beta_0 t} \left(\frac{2\hat{\rho} S_{\max}}{\bar{\rho}_1} + \epsilon_{\max} \right). \quad (40)$$

Combining (28), (31), (33), (33), (37), (39) and (40) leads to

$$\sup_{0 \leq s \leq t} (e^{\beta_0 s} \|\Upsilon(s)\|) \leq \bar{\delta}_1 + \bar{\delta}_2 \sup_{0 \leq s \leq t} (e^{\beta_0 s} \|\Upsilon(s)\|) + e^{\beta_0 t} \bar{\delta}_3 \quad (41)$$

where $\bar{\delta}_1 = \frac{\sqrt{V(0)}}{\sqrt{\lambda_{\min}(P)}}$, $\bar{\delta}_2$ and $\bar{\delta}_3$ are denoted in Theorem 1. When $\bar{\delta}_2 < 1$, it follows from (41) that

$$\sup_{0 \leq s \leq t} (e^{\beta_0 s} \|\Upsilon(s)\|) \leq \frac{\bar{\delta}_1}{1 - \bar{\delta}_2} + e^{\beta_0 t} \frac{\bar{\delta}_3}{1 - \bar{\delta}_2}. \quad (42)$$

For the fact that $e^{\beta_0 t} \|\Upsilon(t)\| \leq \sup_{0 \leq s \leq t} (e^{\beta_0 s} \|\Upsilon(s)\|)$, according to (42), the following expression holds

$$\|\Upsilon(t)\| \leq \frac{\bar{\delta}_1}{1 - \bar{\delta}_2} e^{-\beta_0 t} + \frac{\bar{\delta}_3}{1 - \bar{\delta}_2} \quad (43)$$

which implies that $\|\Upsilon(t)\|$ exponentially converges to a bounded region when $\bar{\delta}_2 < 1$.

Step 2: The jump dynamics at the instant $t_{k+1}h$:

With $V(t)$ in mind, one obtains

$$\begin{aligned} \Delta V &= \Upsilon^T(t) P \Upsilon(t) - \Upsilon^T(t_{k+1}^- h) P \Upsilon(t_{k+1}^- h) \\ &+ V_1(W_F(t)) - V_1(W_F(t_{k+1}^- h)), t = t_{k+1}h. \end{aligned} \quad (44)$$

By (43), it follows that $\|\Upsilon(t)\|$ is bounded, and furthermore, $\Upsilon(t) = \Upsilon(t_{k+1}^- h)$ at jump event-triggered instant $t_{k+1}h$, which means that $\Delta V = V_1(W_F(t)) - V_1(W_F(t_{k+1}^- h))$, $t = t_{k+1}h$ holds. Then, from Lemma 2, one knows that $\Delta V \leq -\frac{\bar{\rho}_1}{2} \|\tilde{W}_F(t_{k+1}^- h)\|^2 + \hat{\rho}$, which implies that the jump dynamics converges to a bounded. Therefore, the stability analysis of the autonomous vehicle (2) under the proposed DMETS (7) can be obtained. The proof is complete. ■

Remark 8: In the simulation, the control parameter K , the observer parameter H , the learning rates ρ_1 , ρ_2 and the gains ξ_1 , ξ_2 need to be specified; the other gain P is only used for stability analysis. From Theorem 1, it is clear that by choosing appropriate gains K and H , $A + HK$ and $\tilde{A} + H\tilde{C}$ become Hurwitz matrices. Then, the condition (23) can always be satisfied when the sampling period is sufficiently small and learning rates are properly tuned. Additionally, if h is selected to be small enough, the boundary in (43) can be made arbitrarily small, further contributing to system stability.

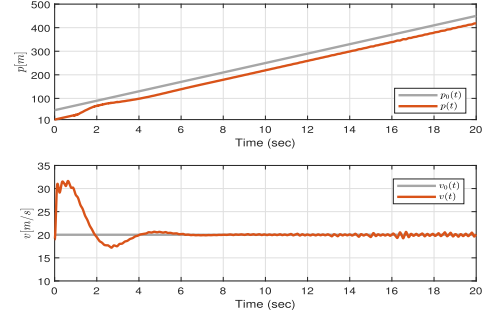


Fig. 2. Curves of position and velocity of the vehicles under Case 1.

The flowchart of the proposed METC strategy has been shown in Fig. 6.

V. SIMULATION EXAMPLE

To examine the advantages of the designed periodic METC approach, the autonomous vehicles are employed. Similar to [40], the parameters of automated vehicles are listed as: $\eta = 0.35$, $T_v = 1$, $\iota = 5$ m, $d_m = 5$ m. For DMETS (7), the parameters are chosen as: the sampling period $h = 0.002$ s, $\xi_1 = 0.01$, $\xi_2 = 0.001$, $\alpha_1 = 0.5$, $\alpha_2 = 0.3$, $\alpha_3 = 0.2$, $\sigma_0 = 0.3$. For deception attacks, the deceptive information is selected to be $g(\bar{\chi}(t_k h)) = \sqrt{\bar{\chi}_1^2(t_k h) + \bar{\chi}_2^2(t_k h) + \bar{\chi}_3^2(t_k h)} \sin(\pi t/20) + \sin(\pi t/5)$, $S(\bar{v}^T \bar{\chi}(t_k h)) = \tanh(\bar{v}^T \bar{\chi}(t_k h))$ and the initial NN weights $\bar{v} \in \mathbb{R}^{4 \times 30}$ and $\tilde{W}_F \in \mathbb{R}^{30}$ are randomly distributed in interval $[0, 0.1]$ with 30 NN nodes. The parameters of NN weight law are chosen as $\rho_1 = 0.98$, $\rho_2 = 0.03$.

To evaluate the effectiveness of the designed periodic METC approach, three cases are provided: Case 1 with the static event-triggered scheme (SETS) [9]; Case 2 with the dynamic event-triggered scheme (DETS) [26]; and Case 3 with the proposed DMETS combined with the periodic METC strategy. These cases enable a systematic comparison of tracking accuracy, estimation performance and communication efficiency. The simulation values contain the initial states and the disturbance of road conditions as $[x_1(0); x_2(0); x_3(0)] = [11; 1; 0]$, $[\hat{x}_1(0); \hat{x}_2(0); \hat{x}_3(0); \hat{d}(0)] = [0; 0; 0; 0]$, $[p(0); v(0); a(0)] = [10; 19; 0]$, $[p_0(0); v_0(0); a_0(0)] = [50; 20; 0]$ and $\omega(t) = \begin{cases} 0.2(t-6), & t \in [0, 6) \\ 1, & t \in [6, 10] \end{cases}$, whereas the controller and observer gains are set as $K = [-2, -120, -20; -1.5]$ and $H = [620; 425; 800; 320]$.

Case 1: Under the SETS [9].

In this case, the SETS is employed with static threshold $\sigma = 0.3$. The evolutions of position and velocity of the leader and following vehicle are depicted in Fig. 3, which shows that the follower successfully tracks the leader. Fig. 2 draws the curves of position error x_1 and velocity error x_2 , which decay rapidly and remain bounded within a small range. Fig. 4 shows the response of the estimation errors. The event-triggered instants and intervals of traditional SETS [9] are given in Fig. 5.

Case 2: Under the conventional DETS [26].

In this case, the DETS is directly designed without historical information. Fig. 7 presents the evolutions of position and

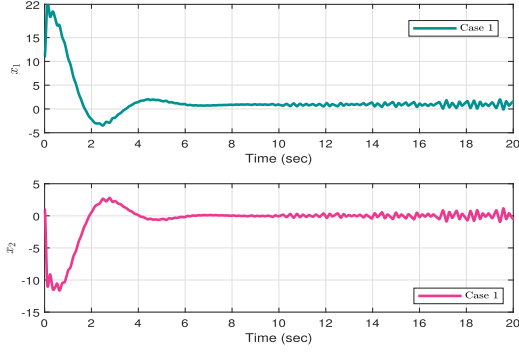


Fig. 3. Curves of position and velocity errors under Case 1.

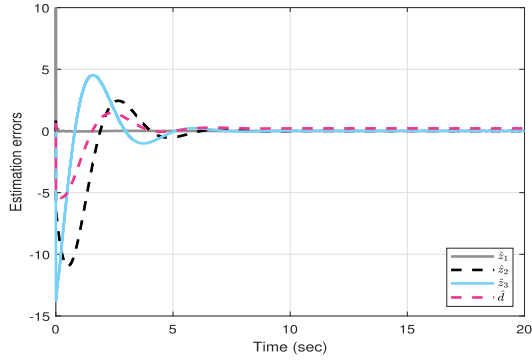


Fig. 4. Curves of estimation errors under Case 1.

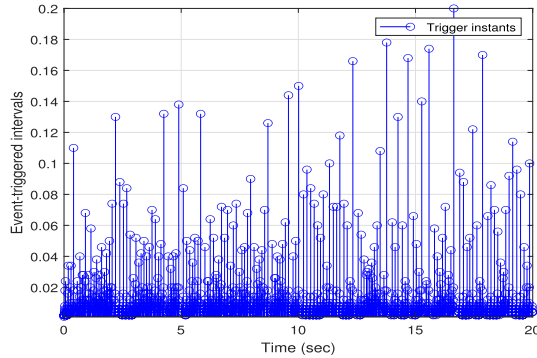


Fig. 5. Evolution of the event-triggered instants and intervals under Case 1.

velocity of the leader and following vehicle. Fig. 8 presents the curves of position error x_1 and velocity error x_2 . The trajectories of estimation errors are plotted in Fig. 9. Fig. 10 depicts the evolution of the event-triggered instants and intervals of the conventional DETS. As shown in Figs. 7–9, the tracking accuracy improves compared with SETS [9], with the velocity error converging to zero after 8 s.

Case 3: The designed periodic METC approach.

Fig. 11 depicts the evolutions of position and velocity of the leader and following vehicle, which means that the follower vehicle achieves trajectory tracking without rear-end collisions. Figs. 12 and 13 present the trajectories of position error x_1 , velocity error x_2 and the estimation errors. The event-triggered instants and intervals of DMETS (7) are illustrated in Fig. 14, which demonstrates that DMETS (7) effectively reduces event-triggered data by 63.2% compared with SETS [9] and 38.8%

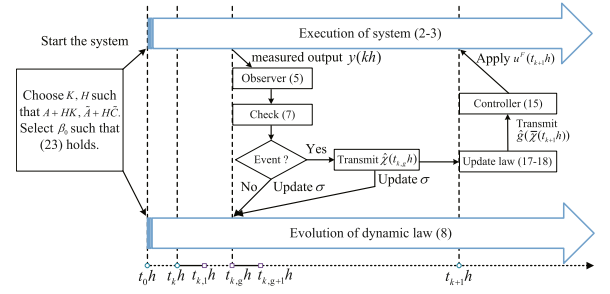


Fig. 6. Flowchart of the proposed METC strategy.

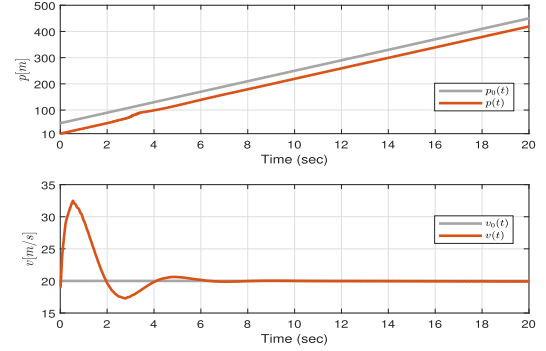


Fig. 7. Curves of position and velocity of the vehicles under Case 2.

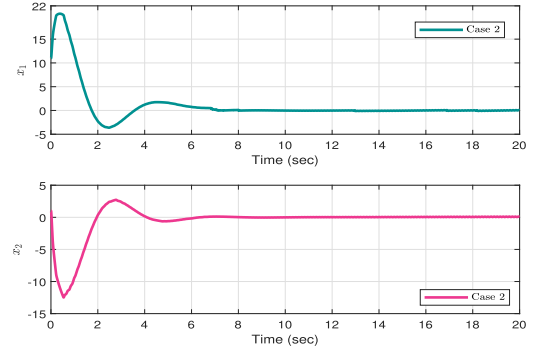


Fig. 8. Curves of position and velocity errors under Case 2.

compared with DETS [26], thereby highlighting its superior efficiency in conserving network bandwidth. Fig. 15 illustrates the deception attacks and their estimation in Case 2 and Case 3, from which one can get that the proposed method achieves more accurate tracking of g by $\hat{g}$. The trajectories of $\|\hat{W}_F\|$ under the DETS [26] and the proposed DMETS are shown in Fig. 16, where the designed periodic METC approach exhibits faster convergence.

Table I summarizes the number of event-triggered data for different thresholds for the SETS [9], DETS [26] and the proposed DMETS (7). It can be seen that DMETS (7) consistently triggers fewer events than SETS and DETS, indicating its superior efficiency in utilizing network resources. As illustrated in Figs. 2–13, Case 3 demonstrates that the designed periodic METC approach not only improves tracking performance and robustness against deception attacks but also significantly reduces communication overhead compared with Case 1 and Case 2.

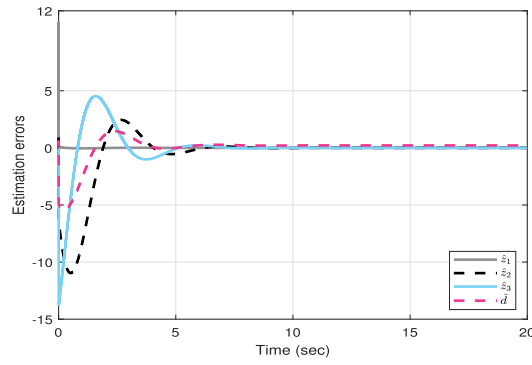


Fig. 9. Curves of estimation errors under Case 2.

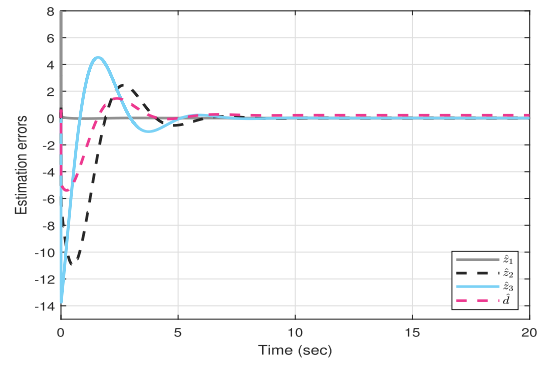


Fig. 13. Curves of estimation errors under Case 3.

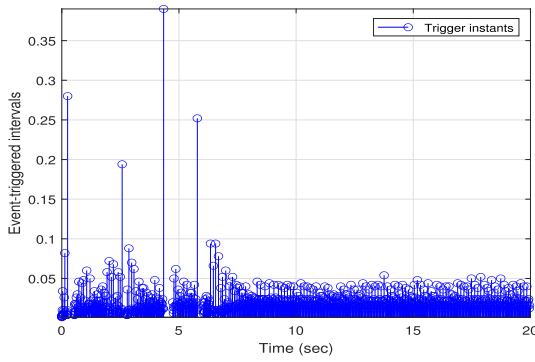


Fig. 10. Curves of the event-triggered instants and intervals under Case 2.

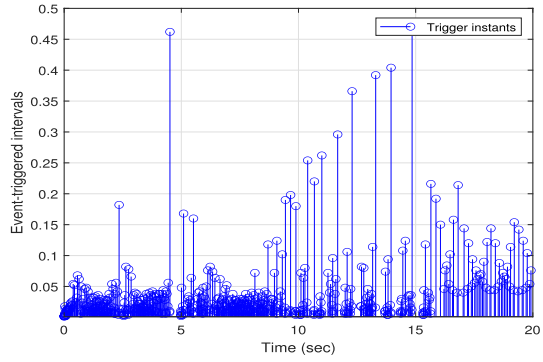


Fig. 14. Curves of the event-triggered instants and intervals under Case 3.

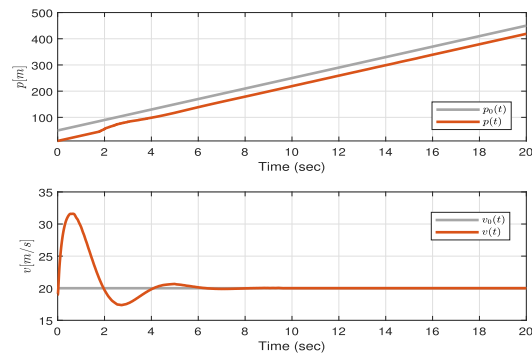


Fig. 11. Curves of position and velocity of vehicles under Case 3.

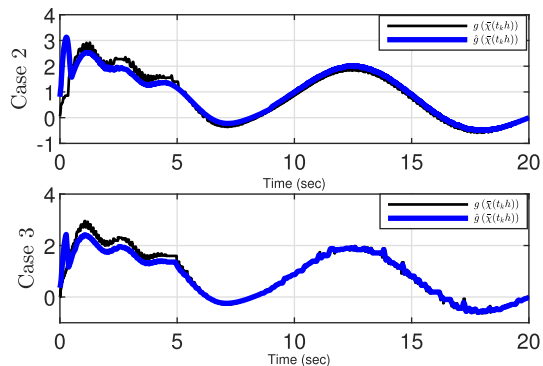
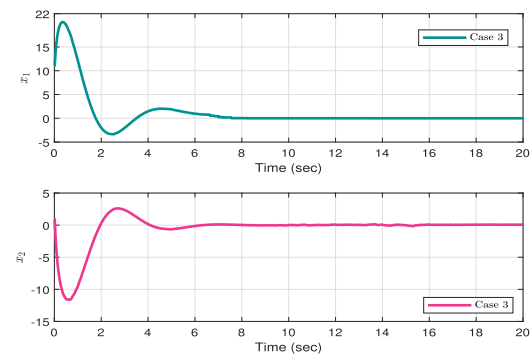

 Fig. 15. Curve of g and $\hat{g}$ under Case 2 and Case 3.


Fig. 12. Curves of position and velocity errors under Case 3.

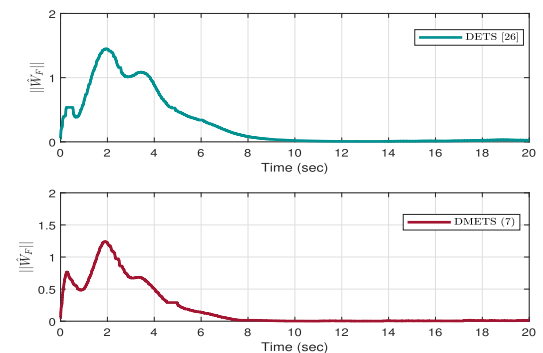

 Fig. 16. Curves of $\|\hat{W}_F\|$ under the DETS [26] and the proposed DMETS.

TABLE I
NUMBERS OF TRIGGERED DATA IN DIFFERENT CASES

Threshold	0.2	0.3	0.5
SETS [9]	1763	1561	1452
DETS [26]	1063	939	609
DMETS in (7)	681	575	401

VI. CONCLUSION

In this article, the observer-based METC problem has been investigated for automated vehicles in the presence of disturbance and deception attacks. To make the compromise between transmission times and disturbance rejection performance, a novel DMETS utilizing the past estimated information and a dynamic threshold has been developed. Based on the state observer and the DMETS, a tracking disturbance rejection controller has been established with past event-triggered data and attack compensation, such that the desired robustness and tracking properties can be enabled. The designed observer-based METC strategy can validly compensate for the impact of deception attacks by applying the NN approach, and significantly weaken the influence of external disturbance by the virtue of the uncertainty estimation method. Moreover, the theorem for ensuring bounded stability of automated vehicles has been given according to the small gain theory. At last, the experiment result has been demonstrated to verify the proposed observer-based METC approach. Future research will focus on developing a dynamic METC framework for heterogeneous vehicle systems under sensor attacks, addressing challenges such as time-varying delays and string stability strategy to enhance system robustness and security.

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