actuators

Article

Adaptive Sliding-Mode Path-Following Control of Cart-Pendulum Robots with False Data Injection Attacks

Jiadong Liu [1], Xiaozheng Jin [1,*], Chao Deng [2] and Weiwei Che [3]

[1] School of Computer Science and Technology, Qilu University of Technology (Shandong Academy of Sciences), Jinan 250353, China
[2] Institute of Advanced Technology, Nanjing University of Posts and Telecommunications, Nanjing 210042, China
[3] Institute of Complexity Science, Qingdao University, Qingdao 266071, China
* Correspondence: xzjin@qlu.edu.cn

Abstract: This paper addresses the displacement path-following problem for a class of disturbed cart-pendulum systems under the fake data injection (FDI) actuator attacks. A filter operator is proposed to estimate the weight vector caused by unknown attacks and disturbances, so that the actuator attacks can be parameterized using neural networks. Then, combined with filter signals and based on adaptive neural network and integral sliding-mode techniques, robust path-following control schemes are proposed to withdraw the impacts of disturbances and FDI attacks. The uniformly ultimately bounded stability results of the closed-loop cart-pendulum system with neural network weight estimations and sliding functions are achieved based on Lyapunov stability theory. Finally, a simulation model of a material robot is used to verify the proposed control strategy.

Keywords: cart-pendulum systems; adaptive neural networks; path-following control; FDI attacks; filter operators; sliding-mode control

check for updates

Citation: Liu, J.; Jin, X.; Deng, C.; Che, W. Adaptive Sliding-Mode Path-Following Control of Cart-Pendulum Robots with False Data Injection Attacks. *Actuators* **2023**, *12*, 24. https://doi.org/10.3390/act12010024

Academic Editor: Hicham Chaoui

Received: 9 December 2022
Revised: 27 December 2022
Accepted: 3 January 2023
Published: 5 January 2023

1. Introduction

As a robotic system with simple structure and fast response, the cart-pendulum robot is widely employed in complex industrial fields, including intelligent manufacturing, agricultural production, logistics, and transportation. The working task of the cart-pendulum robot is often to make the moving path of the car and the deflection angle of the pendulum move along the given reference trajectories, that is, the working task can be considered as the trajectory tracking of the car and pendulum [1,2]. However, due to the widespread application of wireless equipment in the industrial territory, the cart-pendulum robotic system is extremely vulnerable to hacker attacks [3–8]. At the same time, due to the inhomogeneity of the operating ambient, the cart-pendulum robot is also inevitably affected by model uncertainties and external environmental interferences. Therefore, it is of great application significance to ensure that the cart-pendulum robot maintains trajectory tracking under network attacks and external disturbances. In recent years, although many savants have put forward many control methods to deal with the trajectory tracking problem, such as adaptive control [9–11], backstepping control [12–14], sliding-mode control [15–18], and intelligent control [19–21], there are still significant studies to be developed under the consideration of fake data injection (FDI) actuator attacks and interferences.

In the cases of network attacks and external interferences being considered as complex nonlinear disturbances, adaptive control and sliding-mode control with strong robustness have been often combined to combat the disturbances in recent years. The paper [22] proposed an adaptive sliding-mode trace controller for the nonlinear manipulator system to realize the trail following of the manipulator under conditions of uncertain parameters. On the basis of discussing whether the attack can be detected, the paper [23] designed an adaptive sliding-mode observer with a parameter identification function to realize the accurate estimation of the attacks. An adaptive law combining integral sliding-mode control and projection type was proposed in [24], which compensates for the disturbance of model uncertainty, and realizes the tracking of the pitch angle trajectory of the wind-driven generator. The paper [25] estimated the friction effect based on the state observer, combined with sliding-mode technology to realize the path planning of the wheeled mobile robot. In addition, neural networks are widely used in the control problems of nonlinear systems with unmodeled dynamics and parameter uncertainties due to their powerful approximation capabilities. The paper [26] designed an integral sliding-mode control method combined with neural networks to ensure the stability of the system under network attacks. In order to obtain the expected tracking performance, the authors of [27] proposed an adaptive tracking controller, and used the neural network to reimburse the unreliability caused by tire slipping and external disturbance online. Aiming at the uncertainty and nonlinear disturbance of the mobile robot model, a hybrid algorithm combining with neural networks and an adaptive control technique was presented in [28], and the results showed that the algorithm can eliminate the tracking errors under the effects of uncertain parameters and unidentified bounded perturbations.

Through the above research, it can be found that the control problem of the cart-pendulum system under intentional attacks has not been deeply studied. This paper mainly discusses the path-following of the cart-pendulum robot under actuator attacks. First, it is assumed that hackers can obtain information about the system. Additionally, based on that information, they can send false control signals to the actuators, which indicates that false data injection attacks occur [29]. According to the studies in [30–32], it can be known that the attack can be configured in the shape of neural network estimation. However, the adaptive estimation method proposed in [31] can only guarantee that the estimated values of the unknown neural network weights converge to near the true value. Therefore, this paper establishes an adaptive learning framework by introducing a novel filter, and it designs the difference between the entry and egress of the system, which includes the estimation error into the adaptive update law to realize the precise recognition of unknown parameters. In addition, to avoid the chattering phenomenon in the classic sliding-mode process, an integral sliding-mode function is designed, inspired by [33–36], so that the system state is on the sliding-mode appearance from the beginning, clearing up the influence of the approaching phase while maintaining the strong robustness and high precision of the sliding mode control. Combining the above two research methods, a neural network-based adaptively integral sliding-mode strategy is advanced to ensure that the impact of actuator attacks related to state variables of the tracking system can be suppressed while ensuring that the tracking error can be uniformly ultimately bounded. Based on the Lyapunov stability theorem, it is certified that the put forward sliding-mode function and the estimation error for the unknown weights are uniformly ultimately bounded. Finally, the simulation results of an agricultural robot are given to examine the utility of the raised strategy.

In summary, the primary contributions of this paper can be classified as follows:

(1) The existing studies on the tracking error stability of the cart-pendulum system mainly center on the defects caused by the nondeterminacy of system mathematical model, and it is still insufficient to resist the purposeful attack. In this paper, the influence of actuator attack on the system is simulated by using the nonlinear approximation ability of a neural network, and a new control strategy is constructed to ensure that the trajectory tracking is not affected by attacks and disturbances.

(2) The adaptive law proposed in the existing paper [31] can only satisfy that the parameter estimation error is bounded. This paper introduces a filter operator based on the preceding research work, and it proposes an original neural network-based self-adaptive law that achieves an accurate estimation of the unknown weights.

The remaining sections of this paper are as follows. Section 2 establishes the mathematical model of system tracking error and actuator attacks. Section 3 depicts the architecture process of the adaptive integral sliding-mode controller, and the controllability analysis of the proposed control strategy. Section 4 conveys the results of the simulation model. Section 5 summarizes the results.

2. Mathematical Model of the System

This section establishes the dynamics based mathematical model of the cart-pendulum system, establishes the tracking error model of the robot system based on the error with the given reference trajectory, and explains the procedure of framing the actuator attack model by the neural network.

2.1. Cart-Pendulum Robot

Considering that the system is a rigid body, and referring to [37], we can define the following mathematical model based on the dynamics of the cart-pendulum robot:

$$\begin{aligned} &(m_c + M_p)\ddot{x} + M_p l\ddot{\theta}\cos\theta + (c_m + \delta_{cm})\dot{x} - M_p l\dot{\theta}^2\sin\theta = \tau, \\ &M_p l\ddot{x}\cos\theta + (I + M_p l^2)\ddot{\theta} + (c_M + \delta_{cM})\dot{\theta} + M_p g l\sin\theta = 0. \end{aligned} \tag{1}$$

Table 1 gives all of the parameters of the mathematical model, where δ_{cm} and δ_{cM} are the uncertainty estimate error of c_m and c_M. The dynamics after linearization approximation can be rewritten as:

$$D\ddot{q} + V\dot{q} + Gq + \omega = E\tau, \tag{2}$$

where $q = [x;\theta]$, $D = (m_c + M_p)I + M_p m_c l^2$, $E = [M_p l^2 + I; -M_p l]$, $V = \begin{bmatrix} c_m(M_p l^2 + I) & -c_M M_p l \\ -c_m M_p l & c_M(m_c + M_p) \end{bmatrix}$, $G = \begin{bmatrix} 0 & -M_p^2 l^2 g \\ 0 & (M_p + m_c)M_p g l \end{bmatrix}$; ω represents the perturbation caused by the complex interference of the external environment and the wrong model parameters, which are presumed to be contained in Hypothesis 1.

Table 1. Introduction to parameters of robot model.

Parameters	Characters	Units
Moving distance of cart	x	m
Rotation angle of pendulum	θ	rad
The moment of inertia	I	$\mathrm{kg \cdot m^2}$
Barycenter distance	l	m
Mass of cart	m_c	kg
Kinematic viscosity coefficient of cart	c_m	Ns/m
Mass of pendulum	M_p	kg
Kinematic viscosity coefficient of pendulum	c_M	Ns/m
Control signal	τ	$\mathrm{N \cdot m}$
Gravitational acceleration	g	$\mathrm{m/s^2}$

Hypothesis 1. *The disturbance ω is bounded and the boundary is restricted by the condition $\|\omega\| \le k_1\|q\| + k_2\|\dot{q}\| + k_3$, where k_1, k_2, k_3 are coefficients with positive value.*

2.2. External Attacks

The external attack considered in this paper is a false data injection attack. It is a spoofing attack that depends on the system state. It injects the attack signal based on false system state into the actuator through the communication between the controller and the actuator, so that the attacker can interfere with the performance of the system output. Therefore, the actuator attack can be described as follows:

$$\tilde{\tau}(t) = \tau(t) + \sigma_{a\tau}(t, e(t)) \tag{3}$$

where $\tilde{\tau}(t)$ denotes the control signals after being attacked; $\sigma_{a\tau}(t, e(t))$ represents the influence of the false system state on the control signal. According to [31], $\sigma_{a\tau}(t, e(t))$ can be approximated by neural networks in the following form:

$$\sigma_{a\tau}(t, e(t)) = \Psi(e(t))W + \delta_f \tag{4}$$

where $\Psi(e(t))$ is the hidden layer activation function of the neural network,which supposedly has been obtained; W is the weights vector about the activation function, and δ_f is the modeling error, which should be bounded.

2.3. Objectives

The control objective in this paper is to achieve path following of the cart-pendulum robot under the attack of the actuator. Assuming that q_d is the target displacement path, it satisfies the following equation:

$$D\ddot{q}_d + V\dot{q}_d + Gq_d = ET, \tag{5}$$

where T is input force of the reference trajectory system. Therefore, the path-following error for the cart-pendulum robot (2) can be expressed as:

$$e(t) = [e_1, e_2]^T = [q - q_d, \dot{q} - \dot{q}_d]^T. \tag{6}$$

Substituting (6) into the dynamics (2) obtains:

$$\begin{cases} \dot{e}_1(t) = e_2, \\ \dot{e}_2(t) = -V_D e_2 - G_D e_1 + E_D \tau - E_D T - \omega_D, \end{cases} \tag{7}$$

where $V_D = D^{-1}V$, $G_D = D^{-1}G$, $E_D = D^{-1}E$, and $\omega_D = D^{-1}\omega$. Therefore, the relationship between the two dynamics can be indicated as follows:

$$\dot{e} = Ae + B\tau - f(e), \tag{8}$$

where $A = \begin{bmatrix} 0 & 1 \\ -G_D & -V_D \end{bmatrix}$, $B = \begin{bmatrix} 0 \\ E_D \end{bmatrix}$, $f(e) = \begin{bmatrix} 0 \\ \ddot{q}_d + V_D\dot{q}_d + G_D q_d + \omega_D \end{bmatrix}$.

Defining $Bd = -f(e)$, the above error tracking equation can be further drafted by:

$$\dot{e} = Ae + B\tau + Bd, \tag{9}$$

It can be seen that the problem of tracking the reference path is transformed into the stability problem of the path-following error system, i.e., $\lim_{t\to+\infty} e_1(t) = 0$, $\lim_{t\to+\infty} e_2(t) = 0$ in the existence of the perturbations and actuator attacks.

Remark 1. *As mentioned in [30], attackers can modify the data in the channel to destroy or to control the output signal. Therefore, it is legitimate to presume that attackers can acquire the time-varying state of system (9) and design attack signals based on this state. It can be seen from (4) and (9) that the interfering signal and the attacked signal exist together. The disturbance is usually a bounded signal, which exists in the actual system in various forms of uncertainty. In contrast, the attacked signal is maliciously injected by the attacker after stealing the system state, which can change with the system state and attack mode.*

As the movement core of the system, the actuator can easily be attacked by hackers, and the system controlled by the actuator after being attacked will show the movement path that the attacker wants. Therefore, this paper develops a stable sliding-mode control method to counteract the interference caused by actuator attacks and ensure the path-following performance of the system.

3. Design of an Adaptive Sliding-Mode Controller

This section brings forward a kind of adaptive sliding-mode control law for the cart-pendulum system. Based on this control law, the cart-pendulum robot can achieve the movement path-following under actuator attacks. Firstly, a linear filter is used to assist in estimating the unconscious weight vector of the external attacks based on neural networks. After obtaining accurate estimation values, a new adaptive sliding-mode controller is purposed, which can ensure that robot system can still achieve path-following in the case of actuator attacks. Finally, the proposed sliding-mode function and weight estimate errors are proven to be uniformly and ultimately bounded.

3.1. Estimates of Unknown Weights

A neural network is a network connected by a large number of nonlinear processing units. It can establish the mapping relationship between nonlinear input and output via learning samples. Therefore, it is widely used in the modeling of nonlinear systems. The estimated value $\hat{\sigma}(e(t))$ of the attack signal $\sigma_{a\tau}$ in (4) is supposed to be represented in the following form:

$$\hat{\sigma} = \Psi(e(t))\hat{W}, \tag{10}$$

where $\hat{W}$ is the estimation of unidentified weight W, and the difference between them is the estimation error $\tilde{W} = W - \hat{W}$. Reducing $\tilde{W}$ can improve the accuracy of parameter identification of attack signals. Therefore, this paper introduces a linear filter operator to auxiliary estimate weight W.

Combining state space Equation (9) and attack signal in (4), a new system dynamic formula can be acquired:

$$\dot{e}(t) = Ae(t) + B\tau(t) + \Upsilon(e(t))W + B\delta_1 \tag{11}$$

where $\Upsilon(e(t)) = B\Psi(e(t))$, $\delta_1 = \delta_f + d$, and it satisfies $\|\delta_1\| \le \delta_r$.

For system dynamics (11), the filtering form of each variable can be defined as follows:

$$\xi\dot{e}_f + e_f = e, \;\; e_f(0) = 0 \tag{12}$$

$$\xi\dot{\tau}_f + \tau_f = \tau, \;\; \tau_f(0) = 0 \tag{13}$$

$$\xi\dot{\Upsilon}_f + \Upsilon_f = \Upsilon, \;\; \Upsilon_f(0) = 0 \tag{14}$$

where ξ is set as a constant with positive value. Substituting the filtered system variables x_f, u_f, and Υ_f into (11), we obtain the dynamics of the linear filtered system as follows:

$$\dot{e}_f(t) = Ae_f(t) + B\tau_f(t) + \Upsilon_f(e(t))W + B\delta_{1f}, \tag{15}$$

where δ_{1f} is the virtual filter variable of δ_1, i.e., $\xi\dot{\delta}_{1f} + \delta_{1f} = \delta_1$. Combined with the filter operator (12) , the filtered dynamics become the following form:

$$\frac{e - e_f}{\xi} - Ae_f - B\tau_f = \Upsilon_f W + B\delta_{1f}. \tag{16}$$

According to the above equations, it can be found that by introducing this linear filter operator, we can avoid using the derivative of the system variable $\dot{e}_f(t)$ for calculation. Additionally, by calculating (12)–(14), we can easily obtain the filtered system variables e_f, τ_f and Υ_f .

As mentioned above, the purpose of this section is to obtain the estimation of the unknown weight vector. By introducing a class of linear filter, we can apply the auxiliary matrix to collect the estimation error of the weight. For this purpose, the following matrix M and vector N are designed as:

$$\dot{M} = -\chi M + \Upsilon_f^T \Upsilon_f, (M(0) = 0) \tag{17}$$

$$\dot{N} = -\chi N + \Upsilon_f^T (\frac{e - e_f}{\xi} - Ae_f - B\tau_f), (N(0) = 0). \tag{18}$$

To simplify the calculation, the coefficient χ is designed as a positive value. Then, we are able to receive the solutions of (17) and (18):

$$M(t) = \int_0^t e^{-\chi(t-r)} \Upsilon_f^T(r) \Upsilon_f(r) d(r), \tag{19}$$

$$N(t) = \int_0^t e^{-\chi(t-r)} \Upsilon_f^T(r) [\frac{e(r) - e_f(r)}{\xi} - Ae_f(r) - B\tau_f(r)] d(r). \tag{20}$$

Then, the weight W can be expressed with M and N, as follows:

$$N = MW - R, \tag{21}$$

$$R = -\int_0^t e^{-\chi(t-r)} \Upsilon_f^T(r) B\delta_{1f}(r) d(r), \tag{22}$$

where R denotes system error dynamics, and it satisfies $\|R\| \le \delta_H$, $\delta_H > 0$. This is because the interference and modeling error mentioned in this paper are bounded, so the error R is also bounded. Using the linear filter and auxiliary matrix, the estimation error of the unknown weight is able to be expressed by the following equation:

$$\Delta = M\hat{W} - N = -M\tilde{W} + R. \tag{23}$$

The adaptive updating law of the estimated weight vector is shown by:

$$\dot{\hat{W}} = -\Phi(\eta\Delta - (LB\Psi)^T S), \tag{24}$$

where Φ is the designed feedback gain matrix, which has a positive value; η is a ratio used to rectification the adaptive law; S is an independently devised integral sliding-mode function which will be proposed later.

Remark 2. *The dynamic Equation (15) of the filter is obtained by combining the dynamic Equation (11) of the tracking error system with the linear filters (12)–(14). In fact, the dynamic Equation (15) can be regarded as a virtual dynamic equation used only for calculation, and it does not represent any physical meaning. The main purpose of designing Equation (15) is to avoid using higher-order parameters to represent the estimation errors of weights. In the actual process, the real system tracking error equation and the filtered dynamic equation depend on each other and work simultaneously.*

Remark 3. *As mentioned in [38], the matrix Υ meets the persistence of excitation (PE) condition. Therefore, the auxiliary matrix M only related to matrix Υ must be a positive definite matrix, i.e., $\lambda_{\min}(M) > \varrho > 0$. By introducing matrices M and N, the parameter estimate error can be expressed as the form of Δ. Finally, the uniformly ultimately bounded results of the estimation error $\tilde{W}$ are obtained by using the Lyapunov function, which proves that the unrevealed parameters of actuator attack based on the neural network can be accurately estimated.*

3.2. Design of an Adaptive Control Scheme

For state space equations with neural networks (11), the following controller strategy is raised to implement the control goal:

$$\tau = \tau_1 + \tau_0 \tag{25}$$

where $\tau_1(t) = Ce(t)$ is a feedback control law related to the system states, which is used to stabilize the sliding surface; C is a gain vector, and the method to obtain C will be introduced at the end of this section; $\tau_0(t)$ is a control law that will be proposed next, which is used to resist actuator attacks and to reduce the impact of external interference.

Sliding-mode control means that the motion state of the system will be limited to moving in the sliding-mode plane to stability. Generally, the starting position of systems is not on the sliding surface, and the state of the system will have a stage from the starting point to the sliding surface. So, traditional sliding-mode control methods are unable to guarantee that the system states always meet the anticipated performance indicators from the initial time to the sliding-mode surface. However, the integral sliding-mode control method can insure that the initial states of the system are already on the sliding-mode surface, so that the system performance and anti-interference capability are improved. In this section, a class of integral sliding-mode functions are designed for the control objectives as follows:

$$S(t) = Le(t) - Le(t_0) - L\int_{t_0}^{t}(A + BC)e(r)d(r), \tag{26}$$

where L is an adjustable vector, which only needs to ensure that $\det(LB) \neq 0$. The derivative of $S(t)$ regarding time is

$$\dot{S}(t) = L\dot{e}(t) - L(A + BC)e(t). \tag{27}$$

Substituting (11) into (27) yields

$$\begin{aligned} \dot{S}(t) =& L(Ae(t) + B\tau(t) + B\Psi(e(t))W + B\delta_1) - L(A + BC)e(t) \\ =& LB[\tau(t) + \Psi(e(t))W + \delta_1] - LBCe(t) \\ =& LB[\tau_0(t) + \Psi(e(t))W + \delta_1]. \end{aligned} \tag{28}$$

Then, the following sliding-mode controller $\tau_0(t)$ is proposed

$$\tau_0(t) = \tau_2(t) + \tau_3(t) \tag{29}$$

where

$$\begin{aligned} \tau_2(t) &= -\hat{\sigma} \\ \tau_3(t) &= -c_1(LB)^T S - c_2\frac{(LB)^T S\|S^T LB\|}{\|(LB)^T S\|^2} \end{aligned} \tag{30}$$

where c_1 and c_2 are the main parameters to be devised soon.

Theorem 1. *When discussing the disturbed cart-pendulum path-following error system (9) under the attack of an actuator which is described by (3) and (4), if the controller given by (25), (29), and (30) is combined by the adaptive law (24) with the integral sliding-mode control (26), the controller gain C can be solved, and there exist positive constants η to make $\eta\lambda_{\min}(M) - \frac{1}{4} > 0$, so that the uniformly ultimately bounded results of the sliding-mode variable of the system and neural network weight vector-estimated error $\tilde{W}$ can be received, which also means that the path-following errors are uniformly ultimately bounded.*

Proof. The Lyapunov function is structured as follows:

$$V_1(t) = \frac{1}{2}S^T S + \frac{1}{2}\tilde{W}^T \Phi^{-1} \tilde{W}. \tag{31}$$

Afterwards, combined controller (30), the derivative of $V_1(t)$ regarding time becomes

$$\begin{aligned} \dot{V}_1 =& S^T \dot{S} + \tilde{W}^T \Phi^{-1} \dot{\tilde{W}} \\ =& S^T[LB(\tau_0(t) + \Psi(e(t))W + \delta_1)] + \tilde{W}^T \Phi^{-1}[\Phi(\eta\Delta - (LB\Psi)^T S)] \\ =& S^T(LB\tau_3 + LB\Psi\tilde{W} + LB\delta_1) + \tilde{W}^T[\eta(-M\tilde{W} + R) - (LB\Psi)^T S] \\ =& - c_1 S^T LB(LB)^T S - c_2 S^T LB \frac{(LB)^T S \|S^T LB\|}{\|(LB)^T S\|^2} + S^T LB\Psi\tilde{W} + S^T LB\delta_1 \\ & - \eta\tilde{W}^T M\tilde{W} + \eta\tilde{W}^T R - \tilde{W}^T (LB\Psi)^T S. \end{aligned} \tag{32}$$

Design $\Lambda = LB$ and select the appropriate correction coefficient η to satisfy $\eta\lambda_{\min}(M) - \frac{1}{4} > 0$. Ensuring that c_2 is chosen to be slightly greater than δ_r, and considering that the inequality $2a^T b \le a^T a + b^T b$ is always established, (32) can be expressed as:

$$\begin{aligned} \dot{V}_1 \le& - c_1\lambda_{\min}(\Lambda\Lambda^T)\|S\|^2 - c_2\|S^T LB\| + \|S^T LB\|\delta_r \\ & - \eta\lambda_{\min}(M)\|\tilde{W}\|^2 + \frac{1}{4}\|\tilde{W}\|^2 + \eta^2\delta_H^2 \\ \le& - c_1\lambda_{\min}(\Lambda\Lambda^T)\|S\|^2 - (\eta\lambda_{\min}(M) - \frac{1}{4})\|\tilde{W}\|^2 + \eta^2\delta_H^2 \\ \le& - \alpha V_1 + \varepsilon, \end{aligned} \tag{33}$$

where $\alpha = \min\{2c_1\lambda_{\min}(\Lambda\Lambda^T), 2((\eta\lambda_{\min}(M) - \frac{1}{4})/\lambda_{\max}(\Phi^{-1}))\}$, and $\varepsilon = \eta^2\delta_H^2$. Since the coefficient c_1 is a positive constant and Φ is a positive definite matrix, α must be a positive number.

Assuming that the system is under ideal conditions, that is, there is no external disturbance and modeling error, i.e., $\delta_H = 0$. According to Lyapunov stability theorem, the sliding-mode trajectory and neural network weight vector estimate error will gradually reach zero.

Define $\varphi = [\|S\| \ \|\tilde{W}\|]^T, \Pi = diag\{\mu_1, \mu_2\}, \mu_1 = c_1\lambda_{\min}(\Lambda\Lambda^T)$, and $\mu_2 = (\eta\lambda_{\min}(M) - \frac{1}{4})$; thus, (33) can be simplified to

$$\begin{aligned} \dot{V}_1 \le& - \mu_1\|S\|^2 - \mu_2\|\tilde{W}\|^2 + \varepsilon \\ \le& - \varphi^T \Pi \varphi + \varepsilon. \end{aligned} \tag{34}$$

It is easily discovered that $\dot{V}_1$ is negative when φ satisfies the following requirement

$$\|\varphi\| > \sqrt{\frac{\eta^2\delta_H^2}{\lambda_{\min}(\Pi)}}. \tag{35}$$

Through the above formula, based on Lyapunov stability theorem, when $\|\varphi\| > \sqrt{\frac{\eta^2\delta_H^2}{\lambda_{\min}(\Pi)}}$, the system is convergent, and the system will continue to converge until $\|\varphi\| \le \frac{\eta\delta_H}{\sqrt{\lambda_{\min}(\Pi)}}$, which means that the sliding-mode function S and the estimation error $\tilde{W}$ designed in this paper can reach the final state that is ultimately uniformly bounded when φ meets the specific conditions, and the boundary is obtained by $\|\varphi\| \le \frac{\eta\delta_H}{\sqrt{\lambda_{\min}(\Pi)}}$. Therefore, it can be concluded that the system error δ_H and the correction coefficients η and c_1 can affect the boundary of the sliding-mode function S and the convergence of the estimation errors $\tilde{W}$. □

Remark 4. *As a parameter vector L that can be independently designed in the sliding-mode function, it only needs to make $\det(LB) \neq 0$, which means L is not unique. It can be seen from the error convergence boundary obtained above that the smaller the eigenvalue of vector L is, the larger the error convergence boundary obtains. Therefore, an appropriate vector L should be selected to make the error converge within a smaller boundary.*

When designing control law (30), the selected coefficient c_2 should be slightly greater than δ_r. In fact, δ_r is unknown in this system, so the control law (30) should be rewritten as follows:

$$\tau_3(t) = -c_1(LB)^T S - \hat{\delta}_r \frac{(LB)^T S\|S^T LB\|}{\|(LB)^T S\|^2}. \tag{36}$$

The following adaptive update law is designed to estimate δ_r as:

$$\dot{\hat{\delta}}_r = r(\|S^T LB\| - \alpha\hat{\delta}_r). \tag{37}$$

Based on the rewritten control law (36), the following result is obtained:

Corollary 1. *When discussing the disturbed cart-pendulum path-following error system (9) under the attack of an actuator that is described by (3) and (4), if the controller given by (25), (29), and (36) combined by the adaptive law (24), (37) with the integral sliding-mode control (26), the controller gain C can be solved, and there exist positive constants η to make $\eta\lambda_{\min}(M) - \frac{1}{4} > 0$, so the uniformly ultimately bounded results of the sliding-mode variable of the system, the estimated error of interference δ_r, and the neural network weight vector-estimated error $\tilde{W}$ can be received with any limited initial values.*

Proof. The Lyapunov function is structured as follows:

$$V_2(t) = \frac{1}{2}S^T S + \frac{1}{2}\tilde{W}^T \Phi^{-1}\tilde{W} + \frac{1}{2}r^{-1}\tilde{\delta}_r^2, \tag{38}$$

where $\tilde{\delta}_r = \hat{\delta}_r - \delta_r$. Combining the controller (36) and differentiating $V_2(t)$ regarding time, we have

$$\begin{aligned}
\dot{V}_2 =& S^T\dot{S} + \tilde{W}^T\Phi^{-1}\dot{\tilde{W}} + \tilde{\delta}_r\dot{\tilde{\delta}}_r \\
=& S^T[LB(\tau_0(t) + \Psi(e(t))W + \delta_1)] + \tilde{W}^T\Phi^{-1}[\Phi(\eta\Delta - (LB\Psi)^T S)] + \tilde{\delta}_r\dot{\hat{\delta}}_r \\
=& S^T(LB\tau_3 + LB\Psi\tilde{W} + LB\delta_1) + \tilde{W}^T[\eta(-M\tilde{W} + R) - (LB\Psi)^T S] + \tilde{\delta}_r\dot{\hat{\delta}}_r \\
=& -c_1 S^T LB(LB)^T S - \hat{\delta}_r S^T LB\frac{(LB)^T S\|S^T LB\|}{\|(LB)^T S\|^2} + S^T LB\Psi\tilde{W} + S^T LB\delta_1 \\
& - \eta\tilde{W}^T M\tilde{W} + \eta\tilde{W}^T R - \tilde{W}^T(LB\Psi)^T S + \tilde{\delta}_r\dot{\hat{\delta}}_r.
\end{aligned} \tag{39}$$

Combined with the updated adaptive law (37), and with the other parameters being the same as those in Theorem 1, (39) can be expressed as:

$$\begin{aligned}
\dot{V}_2 \leq& -c_1\lambda_{\min}(\Lambda\Lambda^T)\|S\|^2 - \hat{\delta}_r\|S^T LB\| + \|S^T LB\|\delta_r + \tilde{\delta}_r\dot{\hat{\delta}}_r \\
& - \eta\lambda_{\min}(M)\|\tilde{W}\|^2 + \frac{1}{4}\|\tilde{W}\|^2 + \eta^2\delta_H^2 \\
=& -c_1\lambda_{\min}(\Lambda\Lambda^T)\|S\|^2 - \tilde{\delta}_r\|S^T LB\| + \tilde{\delta}_r\dot{\hat{\delta}}_r \\
& - \eta\lambda_{\min}(M)\|\tilde{W}\|^2 + \frac{1}{4}\|\tilde{W}\|^2 + \eta^2\delta_H^2 \\
=& -c_1\lambda_{\min}(\Lambda\Lambda^T)\|S\|^2 - \alpha\tilde{\delta}_r^2 - \alpha\tilde{\delta}_r\delta_r \\
& - \eta\lambda_{\min}(M)\|\tilde{W}\|^2 + \frac{1}{4}\|\tilde{W}\|^2 + \eta^2\delta_H^2
\end{aligned}$$

$$\begin{aligned}
&\leq -c_1\lambda_{\min}(\Lambda\Lambda^T)\|S\|^2-\frac{1}{2}\alpha\tilde{\delta}_r^2+\frac{1}{2}\alpha\delta_r^2\\
&\quad -\eta\lambda_{\min}(M)\|\tilde{W}\|^2+\frac{1}{4}\|\tilde{W}\|^2+\eta^2\delta_H^2\\
&=-c_1\lambda_{\min}(\Lambda\Lambda^T)\|S\|^2-(\eta\lambda_{\min}(M)-\frac{1}{4})\|\tilde{W}\|^2-\frac{1}{2}\alpha\tilde{\delta}_r^2+\eta^2\delta_H^2+\frac{1}{2}\alpha\delta_r^2\\
&\leq -\beta V_2+\varepsilon.
\end{aligned} \tag{40}$$

where $\beta=\min\{2c_1\lambda_{\min}(\Lambda\Lambda^T),2((\eta\lambda_{\min}(M)-\frac{1}{4})/\lambda_{\max}(\Phi^{-1})),\alpha\}$, and $\varepsilon=\eta^2\delta_H^2+\frac{1}{2}\alpha\delta_r^2$. This is the same as the proof process of Theorem 1; since c_1 and α are positive, and Φ is a positive definite matrix, β is also a positive number.

Similarly, according to the Lyapunov stability theorem, when the system is under the ideal condition without interference, i.e., $\delta_H=0$, $\delta_r=0$, the sliding-mode surface and the estimate error of the neural network weight vector will gradually reaches to zero. Considering the system in the real situation, we have the following conclusion:

Define $\varphi=[\|S\|,\|\tilde{W}\|,\tilde{\delta}_r]^T$, and $\Pi=diag\{\mu_1,\mu_2,\mu_3\}$, where $\mu_1=c_1\lambda_{\min}(\Lambda\Lambda^T)$, $\mu_2=(\eta\lambda_{\min}(M)-\frac{1}{4})$, $\mu_3=\frac{1}{2}\alpha$, then (40) can be expressed as

$$\begin{aligned}
\dot{V}_2&\leq -\mu_1\|S\|^2-\mu_2\|\tilde{W}\|^2-\mu_3\tilde{\delta}_r^2+\varepsilon\\
&\leq -\varphi^T\Pi\varphi+\varepsilon.
\end{aligned} \tag{41}$$

This proves that $\dot{V}_2$ is negative when φ satisfies the following requirement

$$\|\varphi\|>\sqrt{\frac{\eta^2\delta_H^2+\frac{1}{2}\alpha\delta_r^2}{\lambda_{\min}(\Pi)}}. \tag{42}$$

According to the above proof, based on Lyapunov stability theorem, when $\|\varphi\|>\sqrt{\frac{\eta^2\delta_H^2+\frac{1}{2}\alpha\delta_r^2}{\lambda_{\min}(\Pi)}}$, the system is convergent, and the system will continue to converge until $\|\varphi\|\leq\sqrt{\frac{\eta^2\delta_H^2+\frac{1}{2}\alpha\delta_r^2}{\lambda_{\min}(\Pi)}}$, so we obtain the conclusion that the sliding curve S, the estimate error $\tilde{W}$ of neural network weight and estimate error $\tilde{\delta}_r$ are uniformly ultimately bounded, and the boundary is determined by $\|\varphi\|\leq\sqrt{\frac{\eta^2\delta_H^2+\frac{1}{2}\alpha\delta_r^2}{\lambda_{\min}(\Pi)}}$. □

The above two proofs ensure that the initiated control scheme can make the tracking error of the robot and the estimation error of the unknown parameter achieve a uniformly ultimately bounded state, which implies that the estimated and the true values of the parameter are equal as long as the time is long enough. On this basis, we only require the estimated value of the unknown parameters to be bounded rather than specified to the true value itself, and so the adaptive laws in (24) and (37) are respectively rewritten as the following form:

$$\dot{\hat{W}}=-\Phi(LBH)^TS, \tag{43}$$

and

$$\dot{\hat{\delta}}_r=r\|S^TLB\|. \tag{44}$$

Then, based on the rewritten adaptive update law, the following Corollary 2 can be obtained.

Corollary 2. *When discussing the disturbed cart-pendulum path-following error system (9) under the attack of an actuator that is described by (3) and (4), if the controller given by (25), (29), and (36) is combined by the adaptive laws (43) and (44) with the integral sliding-mode control (26),* *the controller gain C can be solved, so the sliding-mode variable S and the system path-following error can reach zero in infinite time.*

Proof. Selecting the following Lyapunov function structure

$$V_3(t) = \frac{1}{2}S^T S + \frac{1}{2}\tilde{W}^T \Phi^{-1}\tilde{W} + \frac{1}{2}r^{-1}\tilde{\delta}_r^2, \tag{45}$$

and substituting formulas (36) and (43) into the time derivative of $V_3(t)$, we yield:

$$\begin{aligned} \dot{V}_3 =& S^T \dot{S} + \tilde{W}^T \Phi^{-1}\dot{\tilde{W}} + \tilde{\delta}_r \dot{\tilde{\delta}}_r \\ =& S^T [LB(\tau_0(t) + \Psi(e(t))W + \delta_1)] + \tilde{W}^T \Phi^{-1}\dot{\tilde{W}} + \tilde{\delta}_r \dot{\tilde{\delta}}_r \\ =& S^T (LB\tau_3 + LB\Psi\tilde{W} + LB\delta_1) - \tilde{W}^T (LB\Psi)^T S + \tilde{\delta}_r \dot{\tilde{\delta}}_r \\ =& -c_1 S^T LB(LB)^T S - \hat{\delta}_r S^T LB \frac{(LB)^T S \|S^T LB\|}{\|(LB)^T S\|^2} + S^T LB\delta_1 + \tilde{\delta}_r \dot{\tilde{\delta}}_r. \end{aligned} \tag{46}$$

Combining with the adaptive update law (44) yields

$$\begin{aligned} \dot{V}_3 \leq& -c_1 \|S^T LB\|^2 - \hat{\delta}_r \|S^T LB\| + \|S^T LB\| \delta_r + \tilde{\delta}_r \dot{\tilde{\delta}}_r \\ =& -c_1 \|S^T LB\|^2 - \tilde{\delta}_r \|S^T LB\| + \tilde{\delta}_r \dot{\tilde{\delta}}_r \\ =& -c_1 \|S^T LB\|^2 \leq 0. \end{aligned} \tag{47}$$

It can be easily seen from (47) that when $\|S^T LB\| \neq 0$, $\dot{V}_3(t) < 0$, which means that $V_3(0)$ and $V_3(\infty)$ are bounded. Integrating (47), we obtain

$$\int_0^\infty \|S^T LB\|^2 dr \leq \frac{V_3(0) - V_3(\infty)}{c_1}. \tag{48}$$

Since $S^T LB$ is of uniform continuity and $V_3(0)$ and $V_3(\infty)$ are bounded, the conclusion that $\lim_{t\to\infty} \|S^T LB\| = 0$ can be drawn based on Barbalat lemma. Therefore, the global asymptotical stability of the path-following system can be proven. □

From Corollary 2, it can be known that the path-following error will eventually reach the sliding surface. Therefore, for the gain vector C, it can be obtained that assuming the sliding-mode surface is in perfect sliding status, (i.e., for the sliding-mode function S proposed in (26), assuming that $S(t) = \dot{S}(t) = 0$), the following formula can be obtained

$$\begin{aligned} \dot{S}(t) =& L\dot{e}(t) - L(A + BC)e(t) \\ =& L(Ae(t) + B\tau(t) + B\Psi(e(t))W + B\delta_1) - L(A + BC)e(t) = 0. \end{aligned} \tag{49}$$

Then, we obtain the control input under the ideal sliding state

$$\tau_{ie}(t) = Ce(t) - \Psi(e(t))W - \delta_1. \tag{50}$$

Substituting the equivalent control input (50) into the dynamic equation of the system following error (11), we yield

$$\dot{e}(t) = (A + BC)e(t). \tag{51}$$

Define a positive-definite matrix P. The sliding-mode variable is stable if P satisfies the requirement as:

$$(A + BC)^T P + P(A + BC) < 0. \tag{52}$$

Select the following Lyapunov function structure:

$$V_4(t) = e^T P e \tag{53}$$

Substituting (51) into the Lyapunov function after differentiating, we have

$$\dot{V}_4(t) = e^T[(A + BC)^T P + P(A + BC)]e < 0, \tag{54}$$

which completes the proof.

It follows from the condition (52) that P needs to be satisfied. Define $\bar{P} = P^{-1}$, $Q = CP^{-1}$, and then (52) can be rewritten into the following form

$$\bar{P}A^T + Q^T B^T + A\bar{P} + BQ < 0. \tag{55}$$

By solving the above linear matrix inequality, we can obtain the gain matrix C as

$$C = Q\bar{P}^{-1}. \tag{56}$$

4. Simulation Results

A simulation model of an agricultural cart-pendulum robot is exploited to examine that the raised control strategy has a suppressive effect on actuator attacks and model uncertainties in this section. According to [37], the parameters of the robot are selected as m_c = 18.04 kg, M_p = 4.06 kg, c_m = 44.84 Ns/m, c_M = 0.0015 Ns/m, l = 0.2 m, I = 0.14 kgm^2. The starting path-following error is chosen by $e(0)$=[0.5; 0.7; 0.3; $-$0.1]. For actuator attacks simulated by the neural network (4), W=[$-$0.2; $-$0.5; $-$0.07; 0.1] is chosen as the unknown weight of the neural network. The non-ideal perturbation factor affecting the system is chosen as ω_d = 0.02sin$(e(1)t)$.

The coefficients of the linear filter are $\xi = 0.01$, $\chi = 1$. The parameters of the adaptive update law (24) are set by $\Phi = diag(25, 25, 25, 25)$ and $\eta = 1.6$. Considering the integral sliding-mode function presented as (26), we chose $L = [4.635 \quad 2.684 \quad 0.271 \quad 0.099]$, and by solving the linear matrix inequality (55), we obtain the gain vector of the sliding-mode function $C = [-1.3575 \quad 16.3959 \quad -4.5989 \quad 0.0090]$. Tuning the parameters of the adaptive control strategy, (25) can be calculated as $c_1 = 0.25$ and $c_2 = 1.7$. For the reference path, $T = 5\sin(t)$ is chosen as the tracking signal. Based on the values selected above, the simulation result of the control strategy proposed for resisting actuator attacks is offered as follows.

The simulation is carried out by using SIMULINK/MATLAB software, version R2021a. In the simulation, Figure 1 describes the reference path and the actual path of the cart-pendulum robot, which shows that the moving distance of the cart and the swinging angle of the pendulum can track the reference path respectively, achieving the control goal of this paper. Figure 2 depicts the path-following error of the cart-pendulum system, indicating that the error tracking system is asymptotically stable, and it proves that the raised control scheme (25) can automatically compensate for the impact of actuator attacks, so that the following error converges in the minimum space close to zero. Figure 3 shows the trajectory of the sliding-mode function, indicating that the sliding-mode trajectories eventually converge to the region close to the origin. Figure 4 shows the estimated weight of the neural network, indicating that the estimated value of the unknown weight can be accurately obtained through the adaptive update law (24), and that the weight estimation error is ultimately bounded. Figures 3 and 4 validate the conclusion that the weight estimation error of the neural network and the sliding-mode trajectory are ultimately uniformly bounded. Figure 5 shows the input force acting on the cart-pendulum system. Through the above simulation diagrams, it is proven that all error values are bounded and convergent, and that the path-following performance of the vehicle swing system under actuator attacks has been verified.

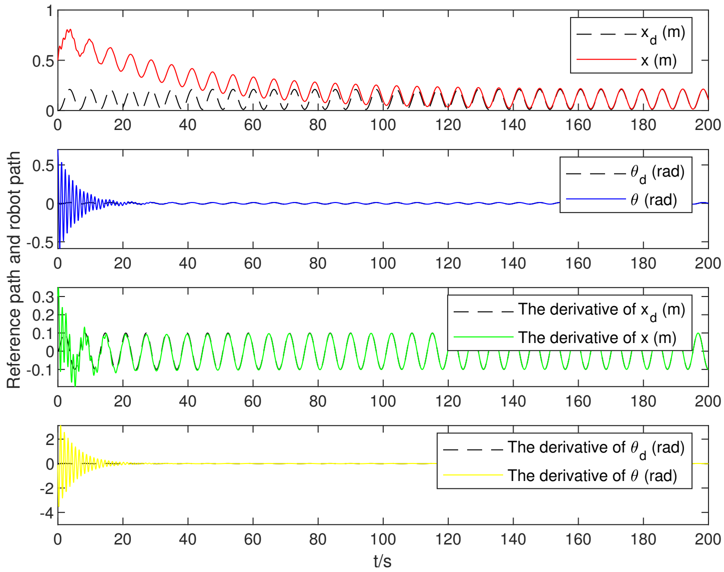

Figure 1. The displacement following paths.

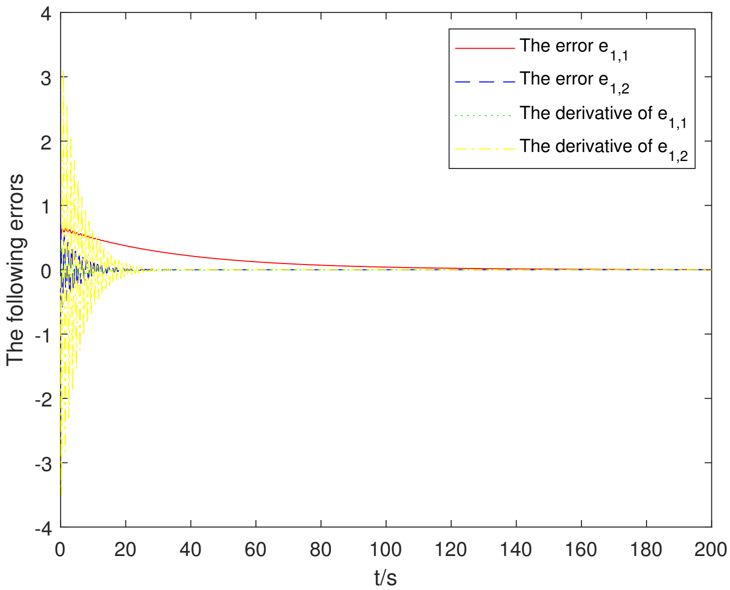

Figure 2. Curves of the following errors $e(t)$ under actuator attacks.

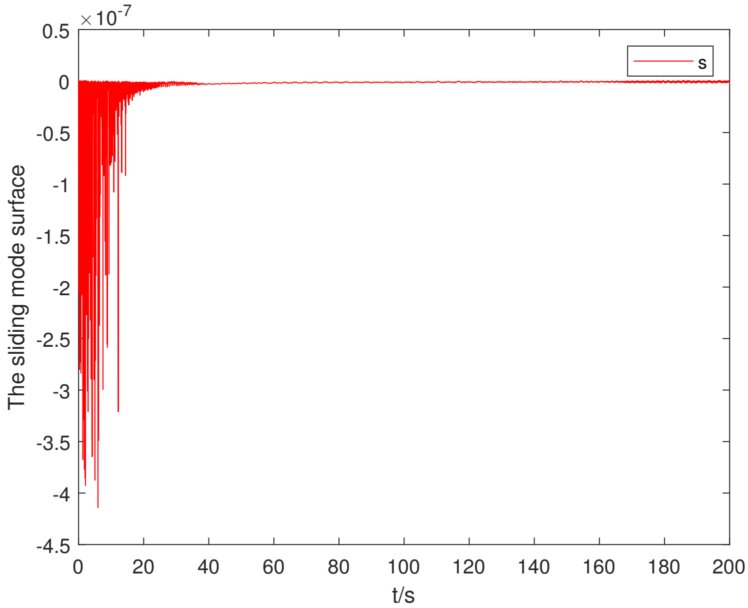

Figure 3. Moving track of the sliding-mode surface $s(t)$.

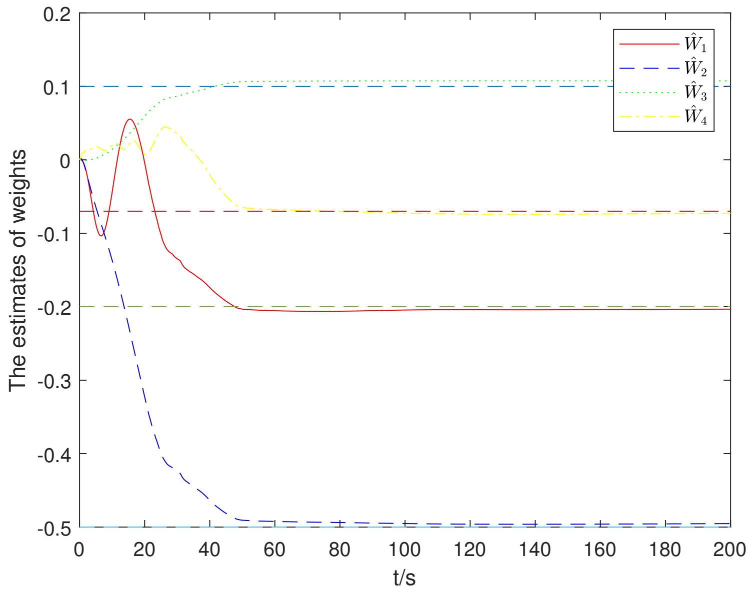

Figure 4. The NN weight estimations and set value.

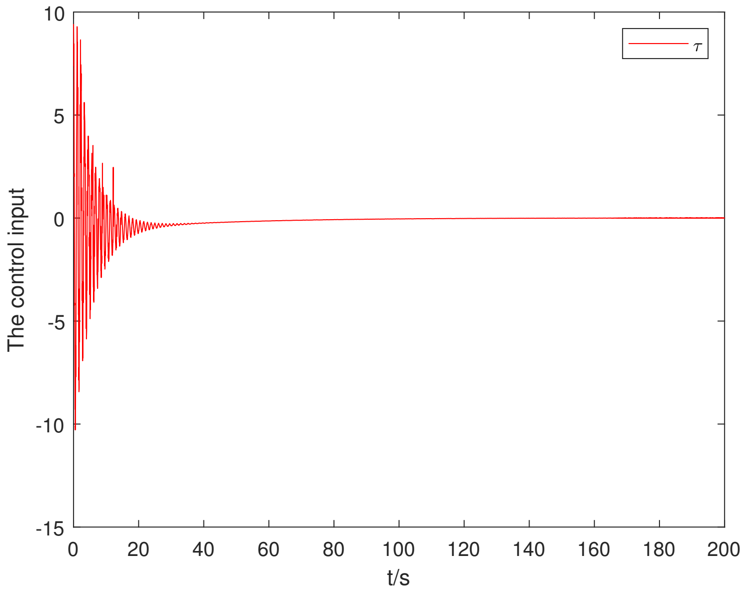

Figure 5. Curves of the force input.

5. Conclusions

This paper has explored the path-following problem of a cart-pendulum robotic system under actuator attacks and uncertainties. The unknown attack signal has been simulated through the neural network, and the accurate estimation of the weights of the neural network have been realized by using the filter. Then, combined with the integral sliding-mode control method, an adaptive integral sliding-mode control scheme has been proposed, which automatically compensates for the effects of disturbances caused by the actuator attacks and uncertainties. A precise tracking of the reference path has been achieved based on Lyapunov stability theory. The utility of the designed controller is confirmed by the simulation results of the agricultural cart-pendulum robot.

Note that the control strategy proposed in this paper can achieve the control objective of the asymptotic tracking of the system. However, in practical applications, it is often required that the tracking system breaks away from the limits of the initial conditions and converges to an equilibrium point in a fixed time. Therefore, we will devote ourselves to developing a fixed-time controller in the future, and we hope to improve the robustness of the controller so that it can resist the attacks of sensors and actuators at the same time.

Author Contributions: Conceptualization, X.J.; Methodology, X.J.; Software, J.L.; Investigation, X.J.; Data curation, J.L.; Writing—original draft preparation, J.L.; Writing—review and editing, X.J. and C.D.; Project administration, X.J.; Funding acquisition, X.J.; Supervision, X.J. and W.C. All authors have read and agreed to the published version of the manuscript.

Funding: This work was supported in part by the National Natural Science Foundation of China under Grant 62173193, Grant 61773149; in part by the Taishan Scholars under Grant tsqn202211208; in part by the Natural Science Foundation of Shandong Province under Grant ZR2020KF034; and in part by the Science Education Industry Integration and Innovation Project under Grant 2022PT025.

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: Data sharing not applicable to this article as no data sets were generated or analyzed during the current study.

Conflicts of Interest: The authors declare no conflicts of interest.

References

1. Shao, Y.; Li, J. Modeling and switching tracking control for a class of cart-pendulum systems driven by DC motor. *IEEE Access* **2020**, *8*, 44858–44866. [CrossRef]
2. Deng, C.; Wen, C.; Wang, W.; Li, X.; Yue, D. Distributed adaptive tracking control for high-order nonlinear multi-agent systems over event-triggered communication. *IEEE Trans. Autom. Control* **2022**. [CrossRef]
3. Vo, A.T.; Kang, H.J. An adaptive terminal sliding mode control for robot manipulators with non-singular terminal sliding surface variables. *IEEE Access* **2018**, *7*, 8701–8712. [CrossRef]
4. Ma, Y.; Che, W.; Deng, C.; Wu, Z. Observer-based event-triggered containment control for MASs under DoS attacks. *IEEE Trans. Cybern.* **2021**, *52*, 13156–13167. [CrossRef]
5. Ma, Y.; Che, W.; Deng, C.; Wu, Z. Distributed model-free adaptive control for learning nonlinear MASs under DoS attacks. *IEEE Trans. Neural Netw. Learn. Syst.* **2021**. [CrossRef]
6. Yang, H.; Ye, D. Observer-based fixed-time secure tracking consensus for networked high-order multi-agent systems against DoS attacks. *IEEE Trans. Cybern.* **2022**, *52*, 2018–2031. [CrossRef] [PubMed]
7. Lu, A.Y.; Yang, G.H. Observer-based control for cyber-physical systems under denial-of-service with a decentralized event-triggered scheme. *IEEE Trans. Cybern.* **2020**, *50*, 4886–4895. [CrossRef] [PubMed]
8. An, L.; Yang, G. Decentralized adaptive fuzzy secure control for nonlinear uncertain interconnected systems against intermittent DoS attacks. *IEEE Trans. Cybern.* **2019**, *49*, 827–838. [CrossRef]
9. Sun, Z.; Zheng, J.; Man, Z.; Wang, H. Robust control of a vehicle steer-by-wire system using adaptive sliding mode. *IEEE Trans. Ind. Electron.* **2015**, *63*, 2251–2262. [CrossRef]
10. Jin, X.; Wang, S.; Qin, J.; Zheng, W.X.; Kang, Y. Adaptive fault-tolerant consensus for a class of uncertain nonlinear second-order multi-agent systems with circuit implementation. *IEEE Trans. Circuits Syst. I Reg. Pap.* **2018**, *5*, 2243–2255. [CrossRef]
11. Jin, X.; Lü, S.; Yu, J. Adaptive NN-based consensus for a class of nonlinear multi-agent systems with actuator faults and faulty networks. *IEEE Trans. Neural Netw. Learn. Syst.* **2022**, *33*, 3474–3486. [CrossRef] [PubMed]
12. Qin, J.; Ma, Q.; Yi, P.; Wang, L. Multiagent interval consensus with flocking dynamics. *IEEE Trans. Autom. Control* **2022**, *67*, 3965–3980. [CrossRef]
13. Shi, P.; Sun, W.; Yang, X.; Rudas, I.; Gao, H. Master-slave synchronous control of dual drive gantry stage with cogging force compensation. *IEEE Trans. Syst. Man Cybern. Syst.* **2022**. [CrossRef]
14. Liu, Z.; Lin, W.; Yu, X.; Rodríguez-Andina, J.J.; Gao, H. Approximation-free robust synchronization control for dual-linear-motors-driven systems with uncertainties and disturbances. *IEEE Trans. Ind. Electron.* **2022**, *69*, 10500–10509. [CrossRef]
15. Brahmi, B.; Laraki, H.; Brahmi, A. Improvement of sliding mode controller by using a new adaptive reaching law: Theory and experiment. *ISA Trans.* **2020**, *97*, 261–268. [CrossRef]
16. Yang, Y.; Chen, F.; Lang, J.; Chen, X.; Wang, J. Sliding mode control of persistent dwell-time switched systems with random data dropouts. *Appl. Math. Comput.* **2021**, *400*, 126087. [CrossRef]
17. El Makrini, I.; Rodriguez-Guerrero, C.; Lefeber, D.; Vanderborght, B. The variable boundary layer sliding mode control: A safe and performant control for compliant joint manipulators. *IEEE Robot. Autom. Let.* **2016**, *2*, 187–192. [CrossRef]
18. Song, Y.; Tang, Y.; Ma, B.; Xu, B. A singularity-free online neural network-based sliding mode control of the fixed-wing unmanned aerial vehicle optimal perching maneuver. *Optim. Control Appl. Methods* **2022**. [CrossRef]
19. Ping, Z.; Zhou, M.; Liu, C.; Huang, Y.; Yu, M.; Lu, J.-G. An improved neural network tracking control strategy for linear motor-driven inverted pendulum on a cart and experimental study. *Neural Comput. Appl.* **2022**, *34*, 5161–5168. [CrossRef]
20. Deng, C.; Jin, X.-Z.; Che, W.-W.; Wang, H. Learning-based distributed resilient fault-tolerant control method for heterogeneous MASs under unknown leader dynamic. *IEEE Trans. Neural Netw. Learn. Syst.* **2021**, *33*, 5504–5513. [CrossRef]
21. Xie, X.; Wei, C.; Gu, Z.; Shi, K. Relaxed resilient fuzzy stabilization of discrete-time Takagi-Sugeno systems via a higher order time-variant balanced matrix method. *IEEE Trans. Fuzzy Syst.* **2022**, *30*, 5044–5050. [CrossRef]
22. Fu, Y.; Sun, N.; Yang, T.; Qiu, Z.; Fang, Y. Adaptive coupling anti-swing tracking control of underactuated dual boom crane systems. *IEEE Trans. Syst. Man Cybern. Syst.* **2021**, *52*, 4697–4709. [CrossRef]
23. Ao, W.; Song, Y.; Wen, C. Adaptive cyber-physical system attack detection and reconstruction with application to power systems. *IET Control Theory Appl.* **2016**, *10*, 1458–1468. [CrossRef]
24. Yin, X.; Zhang, W.; Jiang, Z.; Pan, L. Adaptive robust integral sliding mode pitch angle control of an electro-hydraulic servo pitch system for wind turbine. *Mech. Syst. Signal Pr.* **2019**, *133*, 105704. [CrossRef]
25. Ren, C.; Li, X.; Yang, X.; Ma, S. Extended state observer-based sliding mode control of an omnidirectional mobile robot with friction compensation. *IEEE Trans. Ind. Electron.* **2019**, *66*, 9480–9489. [CrossRef]
26. Lü, S.; Jin, X.; Ding, L.; Tan, Q. Adaptive sliding-mode control of a class of disturbed cyber-physical systems against actuator attacks. *Comput. Electr. Eng.* **2022**, *96*, 107492. [CrossRef]
27. Hoang, N.B.; Kang, H.J. Neural network-based adaptive tracking control of mobile robots in the presence of wheel slip and external disturbance force. *Neurocomputing* **2016**, *188*, 12–22. [CrossRef]
28. Raeisi, Y.; Shojaei, K.; Chatraei, A. Output feedback trajectory tracking control of a car-like drive wheeled mobile robot using RBF neural network. In Proceedings of the 6th Power Electronics, Drive Systems & Technologies Conference (PEDSTC2015), Tehran, Iran, 3–4 February 2015; IEEE: New York, NY, USA, 2015; pp. 363–368.

29. Jin, X.; Che, W.W.; Wu, Z.G.; Wang, H. Analog control circuit designs for a class of continuous-time adaptive fault-tolerant control systems. *IEEE Trans. Cybern.* **2020**, *56*, 4209–4220. [CrossRef] [PubMed]
30. An, L.; Yang, G.H. Improved adaptive resilient control against sensor and actuator attacks. *Info. Sci.* **2018**, *423*, 145–156. [CrossRef]
31. Jin, X.; Haddad, W.M.; Jiang, Z.P.; Kanellopoulos, A.; Vamvoudakis, K.G. An adaptive learning and control architecture for mitigating sensor and actuator attacks in connected autonomous vehicle platoons. *Int. Adapt. Control Signal Process.* **2019**, *33*, 1788–1802. [CrossRef]
32. Jin, X.; Zhao, X.; Yu, J.; Wu, X.; Chi, J. Adaptive fault-tolerant consensus for a class of leader-following systems using neural network learning strategy. *Neural Netw.* **2020**, *121*, 474–483. [CrossRef] [PubMed]
33. Wang, H.; Li, Z.; Jin, X.; Huang, Y.; Kong, H.; Yu, M.; Ping, Z.; Sun, Z. Adaptive integral terminal sliding mode control for automobile electronic throttle via an uncertainty observer and experimental validation. *IEEE Trans. Veh. Technol.* **2018**, *67*, 8129–8143. [CrossRef]
34. Wang, H.; Mi, C.; Cao, Z.; Zheng, J.; Man, Z.; Jin, X.; Tang, H. Precise discrete-time steering control for robotic fish based on data-assisted technique and super-twisting-like algorithm. *IEEE Trans. Ind. Electron.* **2020**, *67*, 10587–10599. [CrossRef]
35. Shao, K.; Zheng, J.; Huang, K.; Wang, H.; Man, Z.; Fu, M. Finite-time control of a linear motor positioner using adaptive recursive terminal sliding mode. *IEEE Trans. Ind. Electron.* **2019**, *67*, 6659–6668. [CrossRef]
36. Shao, K.; Zheng, J.; Wang, H.; Xu, F.; Wang, H.; Liang, B. Recursive sliding mode control with adaptive disturbance observer for a linear motor positioner. *Mech. Syst. Signal Pr.* **2021**, *146*, 107014. [CrossRef]
37. Sakai, S.; Osuka, K.; Fukushima, H.; Iida, M. Watermelon harvesting experiment of a heavy material handling agricultural robot with LQ control. *IEEE/RSJ Int. Conf. Intell. Robot. Syst. IEEE* **2002**, *1*, 769–774.
38. Huang, X.; Dong, J. Reliable control of cyber-physical systems under sensor and actuator attacks: An identifier-critic based integral sliding-mode control approach. *Neurocomputing* **2019**, *361*, 229–242. [CrossRef]