Communication Security of Autonomous Ground Vehicles Based on Networked Control Systems: The Optimized LMI Approach

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Abstract The paper presents a study of networked control systems (NCSs) that are subjected to periodic denial-of-service (DoS) attacks of varying intensity. The use of appropriate Lyapunov-Krasovskii functionals (LKFs) helps to reduce the constraints of the basic conditions and lowers the conservatism of the criteria. An optimization problem with constraints is formulated to select the trigger threshold, which is solved using the gradient descent algorithm (GDA) to improve resource utilization. An intelligent secure event-triggered controller (ISETC) is designed to ensure the safe operation of the system under DoS attacks. The approach is validated through experiments with an autonomous ground vehicle (AGV) system based on the Simulink platform. The proposed method offers the potential for developing effective defense mechanisms against DoS attacks in NCSs.

Keywords Networked control system, Autonomous ground vehicle, Cyber security, Optimized LMI approach, Event-triggered control


1 Introduction

The 21st century has seen rapid development in network communication technology, which has revolutionized numerous fields, including industrial control. The integration of control theory, control technology, computer technology, and network communication technology has facilitated the growth of NCSs [1, 2]. NCSs have been extensively utilized in diverse applications, as illustrated in Figure 1, and have emerged as the preferred technology due to the incorporation of communication and computer technology into the Internet-based TCP/IP protocol [3, 4].

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The proposal of NCSs has allowed for the organic combination of regional control nodes and devices, breaking the information island phenomenon of traditional control systems. This approach expands the way information is transmitted and enables the diversification of management, monitoring, and control strategies across different regions while simplifying the system’s design and improving its reliability and flexibility [5, 6]. NCSs offer the favored development direction for future industrial control systems as they can add or delete control inputs and sensors as nodes are added or removed, offering the ability to modify and adapt the system to meet evolving requirements. Recent research on NCSs has focused on information transmission security, covert false data injection attacks, and network protocol and bandwidth selection to ensure that important closed-loop properties are maintained when inserting computer networks into feedback loops [7–9].

In [7], the author studied the information transmission security problem of NCSs. In [8], the design and detection of covert false data injection attacks against NCSs were studied from different perspectives of attackers and defenders. In [9], the authors investigated the choice of network protocols and bandwidth for NCSs to ensure that important closed-loop properties are preserved when inserting computer networks into feedback loops.

The security of NCSs can be classified into three main areas, namely information security, functional safety, and physical security [10]. Initially, functional and physical safety received more attention to prevent equipment or control system failures [11, 12]. Even in the event of equipment failure, the system should still be able to enter a safe, normal operating state. However, with the widespread adoption of internet communication technology in industrial control systems, the significance of information security has become more prominent, and the industry has shifted its focus toward it [13]. Previous studies have proposed various approaches to mitigating the impact of DoS attacks on NCSs. For example, in [4], the authors proposed an improved approach to estimate performance errors caused by DoS attacks in T-S fuzzy NCSs using suitable integral elastic event-triggered mechanisms and improved LKFs. In [14], a resilient event-triggered strategy was proposed for nonlinear NCSs with interval type-2 fuzzy models subject to nonperiodic DoS attacks, which aimed to reduce performance loss. The authors used a new mismatched membership function to simplify the network control structure under DoS attacks. In [15], an event-triggered control method was presented to analyze the impact of DoS attacks on NCSs in two cases: with and without DoS attacks. The authors in [16] proposed the security control problem of NCSs under DoS attacks as a critical research topic. Moreover, Cheng et al. [17] found that DoS attacks are periodic and studied the relationship between DoS periodic attacks and decay rates.

This paper proposes a periodic DoS attack with an attack intensity and studies its impact on NCSs, building upon previous research. The study of DoS attacks is crucial for the security of NCSs due to the increasing prominence of information security issues resulting from the application and development of Internet communication technology in industrial control systems. As a result, there is a growing emphasis on information security in the industry, and researchers are actively developing strategies to mitigate
the impact of DoS attacks on NCSs. Intelligent transportation systems heavily rely on AGVs, which integrate various high-tech technologies that have been the subject of extensive research [18, 19]. AGVs consist of multiple systems and technologies, including expert system planning functions, computer vision, autonomous navigation, and advanced parallel processing. AGVs can make independent judgments and plans, accept tasks in natural language, devise task execution methods, and continuously revise their plans. This design concept enables AGVs to complete tasks autonomously, even in complex terrain [20]. AGV control systems, as a new interdisciplinary field, can benefit from the use of NCSs, a novel type of control technology that relies on the Internet after the industrialized control system [21]. Therefore, combining NCSs with AGV control systems is an area of significant importance for research.

Based on the previous discussion, this paper focuses on the basic theory of NCSs and AGVs and conducts research on information security and ISETC design issues for AGVs. The main contributions to this paper are summarized below:

1. The paper proposes a model for NCSs under periodic DoS attacks with varying attack intensity. Suitable LKFIs are constructed, and an optimized Linear Matrix Inequality (LMI) is used to analyze the stability of NCSs.
2. The paper transforms the selection of the trigger threshold into an optimization problem with constraints and employs GDA to optimize the threshold and ensure maximum utilization of sampling resources.
3. An ISETC is designed for AGV’s network communication. The ISETC is used to analyze the security and stability of the system and ensure that data transmission is not affected by malicious attacks.

**Notation:** Sym{Q} denotes $Q + Q^T$. $R^{m \times n}$ denotes the set of $m \times n$ real matrices. $I_n$ is the $n \times n$ identity matrix. $M > 0$ ($\geq 0$) indicates $M$ is a positive definite matrix. diag{$A_1, A_2, \ldots, A_n$} indicates a diagonal matrix and the diagonal elements are $A_i, i = 1, 2, \ldots, n$. $P^{-1}$ indicates the inverse $P$. $P^T$ is the adjoint transpose of matrix $P$. $R^n$ is the $n$-dimensional Euclidean space.

2 Preliminaries

A. Event-trigger Control and Design of DoS Attacks

In this paper, we focus on the study of NCSs that are subject to external disturbances as follows:

$$\dot{x}(t) = Ax(t) + Bu(t) + C\omega(t),$$

where $x(t) \in R^n$ means the current state vector; $u(t) \in R^m$ is the signal to control the input; the external disturbance is $\omega(t) \in L_2[0, \infty]$; $A, B, C$ are constant matrices.

In addition to external disturbances, this paper also examines the security of NCSs during network communication transmission. Specifically, we focus on the design of an ISETC to address DoS attacks that occur periodically and with varying levels of intensity. To model these attacks, we assume that the system is targeted by hackers at regular intervals, with $t_k h$ representing the instantaneous sampling time point. The DoS attack design is based on prior research [22]:

$$e(t_k h) = \sum_{k=1}^{\infty} g\delta(t - t_k h),$$

where $g$ is attack intensity; $\delta(t - t_k h)$ means Dirac function. The $S = \{t_k h\}_{k=1}^{\infty}$ and $\lim_{k \to \infty} t_k h = \infty$ is periodic attack signals. $\Delta x(t_k h) = x(t_k h^+ - x(t_k h^-)$, where $x(t_k h^+) = \lim_{\ell \to 0^+} x(t_k h + \ell)$ and $x(t_k h^-) = \lim_{\ell \to 0^-} x(t_k h + \ell)$. This paper assumes that $x(t)$ is right continuous, then we get $x(t_k h) = x(t_k h^+)$ and has a left limit and the DoS attack interval is shown in Definition 1.

The ZOH function generates a sequence of control signals where the sampling instant $t_k h$ satisfies $0 = t_0 < t_1 h < t_2 h < \cdots < t_k h < \cdots; t_k h \in [0, \infty)$. Assuming that the sampling period satisfies $0 \leq h_m < t_{k+1} h - t_k h \leq h_1 \leq h_M$, and $\forall k \geq 0$. Then, we assume that $x(t_k h)$ is the value of the current state of the system thread; $x(t_k h)$ is the system threadstate of the last successful transmission of the system. We have

$$e(t_k h) = x(t_k h^+) - x(t_k h),$$

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where $e(t_k h)$ indicates the error between the current thread state of the system and the system thread state of the system’s last successful transmission.

Attacks launched by hackers may cause errors in the trigger control of the system, as shown in Figure 2. To capture the impact of such attacks, we assume that $x(t_k^+ h + \sigma h)$ represents the system thread state at the last successful transmission following a DoS attack. The error is defined as follows:

$$ e(t_k^+ h) = x(t_k^+ h + \sigma h) - x(t_k h), \quad (4) $$

where $\sigma \in \mathbb{N}$, $e(t_k h)$ represents the error between the current state of the system and the last successful transmission state when the hacker attacks.

Based on the above analysis, a new ETC is designed as follows [14]:

$$ t_{k+1}^h = t_k h + \min_{\sigma} \sigma \{ \Theta \geq 0 \}, \quad (5) $$

where

$$ \Theta = e^T(t_k h) \Phi e(t_k h) + \varphi(t_k h) T(t_{k+1}^h) - \rho x(t_k h) \Phi x(t_k h), $$

$$ T(t_{k+1}^h) = e^T(t_k^+ h) \Phi e(t_k^+ h), $$

and $\Phi > 0$ is a weighting matrix; $\rho$ indicates a threshold parameter; $\mathcal{G}$ means attack strength.

![Figure 2. Event-trigger under DoS attacks.](image)

 Defined the delay at every two successful sampling moments $\tau \triangleq t - t_k h$. Then, the control signal is designed as follows:

$$ u(t) = \mathcal{K} x(t_k h), \ t \in [t_k h, t_{k+1}^+ h). \quad (6) $$

Based on the analysis of (1)-(5), we can get the following NSCs:

$$ \dot{x}(t) = \mathcal{A} x(t) + \mathcal{B} \mathcal{K} x(t_k h) + \mathcal{G} \omega(t), \ t \in [t_k h, t_{k+1}^+ h), \quad (7) $$

where $\mathcal{K}$ is a controller gain matrix.

**Remark 1.** We considered the vulnerabilities of the ISETC in the presence of external attacks and proposed a novel approach to mitigate the effects of a periodic DoS attack $\mathcal{G}$ with varying strengths $\mathcal{G}$. Unlike the existing methods proposed in [15, 23], our approach takes into account the attack’s periodicity and strength, which has important implications for developing effective defense mechanisms. By studying the behavior of the system under such attacks, we were able to design a robust and secure ISETC that provides reliable communication in the presence of adversarial interference.

**B. Parameter optimization based on Gradient Descent Algorithm**

Selecting an appropriate threshold parameter $\rho$ is a crucial aspect of trigger threshold design. The optimization of trigger threshold selection is a complex problem that can be formulated as an optimization problem with constraints. Based on optimization methods in several studies [24, 25], we also propose an
optimal scheme for designing and optimizing trigger threshold selection. The main objective of the scheme is to maximize the utilization of the available sampling resources, subject to the satisfaction of system performance and stability constraints. The following constraint problem is posed:

\[
\begin{aligned}
\max_{\rho \in \mathbb{R}^n} & \quad F(\rho), \\
\text{s.t.} & \quad g_k(\rho) \leq 0, k = 1, \ldots, r, \\
& \quad \rho^l \leq \rho \leq \rho^u,
\end{aligned}
\]  

(8)

where \(\rho\) is the threshold parameter that needs to be determined. \(F(\rho) : \mathbb{R}^n \rightarrow \mathbb{R}\) is the objective function. \(g(\rho) : \mathbb{R}^n \rightarrow \mathbb{R}^m\) denotes a vector function for solving inequality constraint problems at \(\rho\). \(\rho^l\) and \(\rho^u\) represent the upper and lower bounds of \(\rho\), respectively.

Then, the gradient descent method is used to optimize the target problem by updating the threshold parameter iteratively. At each iteration, the step length is set as \(\rho_{k+1} = \rho_k + m_k\), where \(m_k\) is the step size and \(l_k\rho_k\) is the descent direction. The optimal threshold parameter is obtained when the objective function reaches its minimum value.

The parameter \(\rho_k\) is necessary for Pareto optimization, as there is no first-order descending direction for all individual goals. For all individual goals, there is no first-order descending direction as follows:

\[
\text{range}(\nabla T_H(\rho_k)) \cap (-\mathbb{R}^n_+) = \emptyset,
\]

(9)

where \(\mathbb{R}^n_+\) is said to the pyramid, \(T_H(\rho_k)\) is \(H\) in \(\rho_k\) of the jacobian matrix. When \(n = 1\), \(l_k = -\nabla h_1(\rho_k)\) for the fastest decline in the direction, which is equivalent to minimizing threshold \(\nabla h_1(\rho_k)l + \frac{1}{2}||l||^2\) in \(l\).

It is proved that the dual of (10) is a sub-problem

\[
\begin{aligned}
\lambda_k & \in \arg \max_{\lambda \in \mathbb{R}^n} \| \sum_{i=1}^n \lambda_i \nabla h_i(\rho_k) \|_2^2, \\
\text{s.t.} & \quad \lambda \in \Delta^n,
\end{aligned}
\]  

(11)

where \(\Delta^n = \{ \lambda : \sum_{i=1}^n \lambda_i, \lambda_i \geq 0, \forall i \in \{1, \ldots, m\} \}\) is a simplex set. According to the theory in [25], we get the following

\[
\exists \sigma \in \Delta^n \rightarrow g_k(\rho) = \sum_{i=1}^n \lambda_i \nabla h_i(\rho_k) = 0.
\]

(12)

Remark 2. In accordance with the approach described in references [24, 25], selecting an appropriate threshold parameter \(\rho\) is crucial for Pareto maximization. To address this problem, we transform the process into an optimization problem, which enables us to iteratively determine the optimal threshold parameter that satisfies the system requirements. By employing the gradient descent algorithm, we accelerate the search for the threshold parameter, resulting in optimized parameters that reduce the trigger rate and save sampling resources. This method has been proven effective in expediting the search process and enhancing the system’s performance.

The Pareto first-order stationary point, denoted as \(\rho_k \in \mathbb{P}\), is obtained by solving the optimization problem in Equation (8) using the proximal gradient algorithm. This iterative algorithm updates the estimate of the Pareto front using the gradient of the objective function and the proximal operator of the regularization term. The proximal operator enforces the constraint that the estimate of the Pareto front belongs to the feasible set \(\mathbb{P}\). The algorithm continues to update the estimate of the Pareto front until convergence is achieved, which is determined by a stopping criterion based on the norm of the difference between successive estimates of the Pareto front. The algorithm also includes a step size parameter \(m_k\), which controls the step size of the gradient descent update. This parameter is chosen using a backtracking
line search that ensures the update decreases the objective function. The specific steps of the algorithm are as follows:

**Algorithm 1:** Select the trigger threshold $\rho$ based on the GDA

| Input: $\rho_k \in [\rho^l, \rho^u] \subseteq S$ and a step size sequence $m_k$ |
| Output: $\rho_{k+1}$ |
| 1 begin |
| 2 for $k = 0, 1, \cdots$ do |
| 3 Compute the gradients |
| 4 $\exists \lambda \in \mathbb{D}^n \rightarrow g_k(\rho) = \sum_{i=1}^{n} \lambda_i \nabla h_i(\rho_k) = 0$ |
| 5 Solve the objective function |
| 6 $\lambda_k \in \arg \max_{\lambda \in \mathbb{R}^n} \| \sum_{i=1}^{n} \lambda_i \nabla h_i(\rho_k) \|^2$ |
| 7 $\lambda \in \{ \lambda : \sum_{i=1}^{n} \lambda_i \geq 0, \forall i = 1, \cdots, m \}$ |
| 8 Iterate the next updates $\rho_{k+1}$ |
| 9 $\rho_{k+1} = \mathbb{P}_S(\rho_k - m_k g_k(\rho))$ |
| 10 end |

**Definition 1** [26] The average Dos attacks interval of the attack time sequence $\vartheta = \{t_1, \cdots, t_k, \cdots \}$ is equal to $T_a$ if there exist $S_0 \geq 0$ and $T_a$, we can get the DoS attacks interval as follow:

$$
\frac{T - t}{T_a} - S_0 \geq N_\vartheta(T, t) \geq \frac{T - t}{T_a} + S_0,
$$

where $\forall T \geq t \geq 0$ and $N_\vartheta(T, t)$ is the total number of times the attack sequence $\vartheta$ has been hacked over the time period $(t, T)$.

**Lemma 1** [27] Given a $x$ satisfies $x : [a, b] \rightarrow \mathbb{R}^n$. And there are the arbitrary matrices $N_1$, $N_2$ and $N_3$ and the matrices $M > 0$. We can get the following inequality holds:

$$
- \int_{a}^{b} e^T M e ds \leq \xi_1^T \Omega \xi_1,
$$

where

$$
\xi_1 = \mbox{col} \left\{ e(b), e(a), \frac{1}{b-a} \int_{a}^{b} e ds, \frac{2}{(b-a)^2} \int_{a}^{b} \int_{a}^{u} e(u) du ds \right\},
$$

$$
\xi_2 = \mbox{col} \left\{ e(b), e(a), \frac{1}{b-a} \int_{a}^{b} e ds, \frac{2}{(b-a)^2} \int_{a}^{b} \int_{a}^{u} e(u) du ds \right\},
$$

$$
\Omega = (b-a) \left( N_1 M^{-1} N_1 + \frac{1}{3} N_2 M^{-1} N_2 + \frac{1}{5} N_3 M^{-1} N_3 \right) + \mbox{sym} \{ (N_1 \vartheta_1 + N_2) \vartheta_2 + N_3 \vartheta_3 \},
$$

$$
\vartheta_1 = e_1 - e_2, \quad \vartheta_2 = e_1 + e_2 - 2e_3, \quad \vartheta_3^2 = e_1 - e_2 - 6e_3 + 6e_4, \quad \vartheta_3 = e_1 - e_2 + 6e_3 - 6e_4.
$$

**3 Main results**

In this section, we consider the scenario where the control gain matrix $\mathcal{K}$ is known and establish the asymptotic stability condition of the system under the designed safe trigger mechanism, which is presented in Theorem 1. We then proceed to design and solve the controller gain matrix in Theorem 2. To simplify the notation, we define the following symbols:

$$
\alpha(t) = \mbox{col} \{ x(t), x(t_kh), x(t_{k+1}h) \}, \quad h_k = t_{k+1}h - t_k, \quad h = t - t_kh, \quad \Pi_1 = \mbox{col} \{ e_1 - e_1 \}, \quad \Pi_2 = \mbox{col} \{ e_1 - e_3 \},
$$
\[\begin{align*}
\Pi_3 &= \text{col}\{e_1, e_3, e_4\}, \quad \Pi_4 = \text{col}\{e_5, 0, 0\}, \quad \Phi = \text{col}\{e_1 - e_2, e_1 + e_2 - 2e_6, e_1 - e_2 + 6e_6 - 12e_7\}, \\
\xi(t) &= \text{col}\{x(t), x(t - \tau), x(t_kh), x(t_{k+1}h), \dot{x}(t), \frac{1}{\tau^2} \int_{t-\tau}^{t} x(s)ds\}, \\
\mathcal{H} &= \text{diag}\{H, 3H, 5H\}, \quad e_i = [0_{n \times (i-1)n} \quad I_{n \times n} \quad 0_{n \times (9-i)}], \quad i = 1, 2, \ldots, 9.
\end{align*}\]

**Theorem 1.** Let \( h, \), \( h_m \), and \( \rho \) be positive scalars. The NCSs given by (7) are asymptotically stable if there exist symmetric matrices \( \mathcal{P}, \mathcal{H}, \) any matrix of suitable dimension \( \mathcal{M}, \mathcal{Q}, \) and \( \mathcal{B}_n \) \((n = 1, 2, 3)\) that satisfy the following LMIs:

\[\mathcal{P} \geq 0, \quad \mathcal{H} > 0, \quad \Xi \leq 0, \quad \text{(13)}\]

where

\[\Xi = \Xi_a + \text{Sym}\{\Gamma \Delta\} + \Theta(\Upsilon(t_{k+1}^+ h)),\]

\[\Xi_a = \text{Sym}\{e_1T \mathcal{P} e_5\} + e_5T \mathcal{P} \Pi_1 - \Pi_1^T \mathcal{M} e_5 + h_k \Pi_3 \mathcal{P} \Pi_3 + \tau e_5T \mathcal{H} e_5 + \Omega,\]

\[\Omega = \Phi \mathcal{H} \Phi, \quad \Gamma = e_1T \mathcal{F}_1 + e_1T \mathcal{F}_2 + e_5T \mathcal{F}_3, \quad \Delta = \mathcal{A} e_1 + \mathcal{B} \mathcal{H} e_3 + \mathcal{C} e_{10} - e_5,\]

\[\Theta(\Upsilon(t_{k+1}^+ h)) = e_8T \Phi e_8 + \mathcal{G} e_9 \Phi e_9 - \sigma e_9^2 \Phi e_3,\]

**Proof.** Given the LKF candidate as

\[V(t) = \sum_{i=1}^{3} V_i(t), \quad \text{(14)}\]

where

\[V_1(t) = x^T(t) \mathcal{P} x(t),\]

\[V_2(t) = (x(t) - x(t_kh)) \mathcal{M} (x(t_{k+1}h) - x(t)) + h_k \alpha(t) \mathcal{H} \alpha(t),\]

\[V_3(t) = \int_{t-\tau}^{t} (s - t + \tau) \dot{x}^T(s) \mathcal{H} \dot{x}(s)ds.\]

We take the derivative of \( V_i(t) \), and we get

\[\dot{V}_1(t) = 2x^T(t) \mathcal{P} \dot{x}(t), \quad \text{(15)}\]

\[\dot{V}_2(t) = \dot{x}(t) \mathcal{M} (x(t_{k+1}h) - x(t)) - (x(t) - x(t_kh)) \mathcal{H} \dot{x}(t) + h_k \alpha^T(t) \mathcal{H} \alpha(t) - h_k \alpha^T(t) \mathcal{P} \alpha(t) + 2h_k \alpha^T(t) \mathcal{H} \alpha(t) + 2h_k \alpha^T(t) \mathcal{P} \alpha(t), \quad \text{(16)}\]

\[\dot{V}_3(t) = \tau \dot{x}^T(t) \mathcal{H} \dot{x}(t) - \int_{t-\tau}^{t} \dot{x}^T(s) \mathcal{H} \dot{x}(s)ds. \quad \text{(17)}\]

Using the integral inequality in Lemma 1, the integral term in (17) can be scaled as follows:

\[\begin{align*}
- \int_{t-\tau}^{t} \dot{x}^T(s) \mathcal{H} \dot{x}(s)ds &\leq - \left[ \begin{array}{c}
x(t) - x(t - \tau) \\
\frac{1}{\tau^2} \int_{t-\tau}^{t} x(s)ds
\end{array} \right]^T \\
&\times \left[ \begin{array}{cc}
\mathcal{H} & 0 \\
0 & 3\mathcal{H}
\end{array} \right] \left[ \begin{array}{c}
x(t) + x(t - \tau) - 2 \int_{t-\tau}^{t} \frac{x(s)ds}{\tau} \\
\frac{1}{\tau^2} \int_{t-\tau}^{t} \frac{x(s)ds}{\tau} - 12 \int_{t-\tau}^{t} \int_{u}^{t} \frac{x(s)ds}{\tau}du
\end{array} \right] \\
&\times \left[ \begin{array}{c}
x(t) - x(t - \tau) \\
\frac{1}{\tau^2} \int_{t-\tau}^{t} x(s)ds
\end{array} \right]. \quad \text{(18)}
\end{align*}\]
Based on the above results, \( \dot{V}_3(t) \) can be rewritten as follows:

\[
\dot{V}_3(t) \leq \tau \dot{x}^T(t) \mathcal{H} \dot{x}(t) + \Omega,
\]

(19)

The constraints of the unsafe ISETC (5) are considered, and the following inequality is obtained:

\[
0 \leq \dot{e}^T(t_k h) \Phi e(t_k h) + \dot{\mathcal{Y}}(t_k h) - \rho x(t_k h) \Phi x(t_k h) = \xi^T(t) \Theta(t) \xi(t).
\]

(20)

Based on the system (7), the following equation is got

\[
0 = 2[\dot{x}^T(t) \mathcal{Y}_1 + \omega^T(t) \mathcal{Y}_2 + \dot{x}^T(t) \mathcal{Z}_3] [\mathcal{A} x(t) + \mathcal{B} u(t) + \mathcal{C} \omega(t) - \dot{x}(t)]
\]

\[
= 2[\dot{x}^T(t) \mathcal{Y}_1 + \omega^T(t) \mathcal{Y}_2 + \dot{x}^T(t) \mathcal{Z}_3] [\mathcal{A} x(t_k h) + \mathcal{C} \omega(t) - \dot{x}(t)]
\]

\[
= \text{Sym}\{\xi^T(t) \Gamma \Delta \xi(t)\}.
\]

According to (14)-(21), the following equation is had as follow

\[
\dot{V}_1(t) \leq \xi^T(t) \Xi \xi(t).
\]

(22)

Based on the linear convex combinations method [28], for all \( \xi^T(t) \Xi \xi(t) < 0 \) are established. We can get

\[
\Xi(t = t_k h) \leq 0, \quad \Xi(t = t_{k+1} h) \leq 0.
\]

(23)

Finally, we can conclude that the NCSs (7) are asymptotically stable if the conditions (11) of Theorem 1 are satisfied and if the inequality \( \dot{V}_1(t) \leq \xi^T(t) \Xi \xi(t) \leq 0 \) holds. This inequality ensures that the LKF \( V(t) \) is decreasing along the system trajectory, and therefore, the system state will converge to the equilibrium point. Thus, the designed safe trigger mechanism ensures the asymptotic stability of the NCSs under the presence of DoS attacks.

Remark 3. Unlike the method in reference [29], the sampling time information is fully considered in the looped function constructed by \( V_2(t) \). It contains both the date information on \( x(t_k h) \) and \( x(t_{k+1} h) \), satisfying \( \lim_{t \to t_{k+1} h} V_2(t) = \lim_{t \to t_{k+1} h} V_2(t) = \lim_{t \to t_{k+1} h} V_2(t) = 0 \). This method introduces more sampling time information based on reducing the initial constraints. Furthermore, increasing the information storage of LKFs reduces the conservatism of the criteria.

Remark 4. Analyzing the computational complexity of control algorithms is essential. In this paper, a loop function is constructed to reduce the initial constraints and therefore decrease the computational complexity of the control algorithm. The resulting algorithm achieves effective control of AGVs with relatively low computational complexity, specifically \( 6n^2 + n \). Moreover, we were able to verify the results within an acceptable time using an Intel(R) Core(TM) i7-8565U CPU @ 1.80GHz 1.99 GHz computer.

The control algorithm considers stability analysis and employs an optimization approach to determine the maximum allowable delay and the controller gain matrix. This guarantees the system’s stability under DoS attacks while minimizing their impact on the system’s performance. Control algorithm 2 is based on the presented stability analysis, and it aims to calculate the maximum allowable delay \( \tau_{\text{max}} \) and the controller gain matrix \( K \) to ensure the system’s stability under DoS attacks. The algorithm is outlined as follows:

\[\text{Algorithm 2: The maximum acceptable time delay } \tau_{\text{max}} \text{ and controller gain matrix } \mathcal{H}\]

\[
\text{Input: } \text{The known positive definite vector } \rho, h_m, h_M, \mu_1, \mathcal{I}, \text{ and } \mu_2
\]

\[
\text{Output: The maximum acceptable time delay } \tau_{\text{max}} \text{ and controller gain matrix } \mathcal{H}
\]

1. Initialize the global counter \( \delta_i \);
2. Reset maximum acceptable time delay \( \tau_{\text{max}} \);
3. for \( \delta_i = 0 : 0.0001 : 1 \) do
   4. \( \mathcal{P} \geq 0, \quad \mathcal{H} > 0, \quad \Xi \leq 0, \)
   5. if There is not a feasible solution then
      6. Replace \( \tau_{\text{max}} \) with \( \tau_{\text{max}} + \delta_i \);
      7. Replace \( \delta_i \) with \( \delta_{i+1} \);
      8. Return Line 4
     else break
    end
6. \[\text{end}\]
Theorem 2. Let $\rho, \mu_1, \mu_2, h_m$, and $h_M$ be positive scalars. Consider the NCSs (7) under the designed safe trigger mechanism. The system is asymptotically stable if there exist symmetric matrices $\tilde{P}, \tilde{H}$, and any matrices $\tilde{M}, \tilde{Q},$ and $W$ that satisfy the following LMIs:

$$\tilde{P} \geq 0, \quad \tilde{H} > 0, \quad \tilde{X} \leq 0,$$

where

$$\tilde{X} = \tilde{X}_a + \text{Sym}\{\tilde{\Gamma} \tilde{\Delta}\} + \tilde{\Theta}(\tilde{\Upsilon}(t_{k+1}^+ h)),
\tilde{X}_a = \text{Sym}\{\tilde{e}_1^T \tilde{P} \tilde{e}_5\} + e_5^T \tilde{H} \tilde{e}_5 + h_k \Pi_3^T \hat{P} \Pi_3 + \tau e_5^T \tilde{H} e_5 + \hat{\Omega},
\tilde{\Omega} = \Phi \tilde{H} \Phi,
\tilde{\Gamma} = e_1^T \hat{P} e_5 + e_5^T \tilde{H} e_5 + \mu_1 e_1^T e_10 + \mu_2 e_5^T e_5,
\tilde{\Delta} = A \tilde{X} e_1 + B \tilde{W} e_3 + C \tilde{X} e_10 - \tilde{X} e_5, \tilde{H} = \text{diag}\{\tilde{H}, 3 \tilde{H}, 5 \tilde{H}\},
\tilde{\Theta}(\tilde{\Upsilon}(t_{k+1}^+ h)) = e_8^T \Phi e_8 + \tilde{G} e_9^T \Phi e_9 - \sigma e_3^T \Phi e_3.$$

Proof: The gain matrix $K = \tilde{W} \tilde{X}^{-1}$ and $\Phi = \tilde{X}^{-T} \tilde{P} \tilde{X}^{-1}$ are defined. Pre-multiplying and post-multiplying (13) by

$$\tilde{Y}_1 = \tilde{X}^{-1}, \quad \tilde{Y}_2 = \mu_1 \tilde{X}^{-1}, \quad \tilde{Y}_3 = \mu_2 \tilde{X}^{-1}, \quad \tilde{P} = \tilde{X}^{-T} \tilde{P} \tilde{X},$$

$$\tilde{H} = \tilde{X}^T \tilde{H} \tilde{X}, \quad \tilde{M} = \tilde{X}^T \tilde{M} \tilde{X}.$$

Then, the LMIs (23) can be obtained. The detailed proof process is similar to Theorem 1.

4 Illustrative example

We conducted simulation experiments on the Simulink joint platform to verify the effectiveness of the proposed control algorithm in this paper, using the data provided in reference [19]. The experimental setup is illustrated in Figure 3, and some data related to the vehicle are shown in Table 1:

![Schematic diagram of path following model.](image)

Table 1. Parameter values of the autonomous ground vehicles

<table>
<thead>
<tr>
<th>Parameter</th>
<th>$m$</th>
<th>$I_s$</th>
<th>$l_n$</th>
<th>$l_m$</th>
<th>$C_n$</th>
<th>$C_m$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Value</td>
<td>1500</td>
<td>2500</td>
<td>1.3</td>
<td>1.4</td>
<td>40000</td>
<td>40000</td>
</tr>
<tr>
<td>Unit</td>
<td>kg</td>
<td>kg</td>
<td>m</td>
<td>m</td>
<td>N/rad</td>
<td>N/rad</td>
</tr>
</tbody>
</table>
The dynamic physics equations for AGV (see Figure 3) can be written as follows:

\[
\begin{align*}
\dot{e} &= v_x \omega + v_x \phi + s_1, \\
\dot{\phi} &= r - \rho(\delta_c) v_x, \\
\dot{\omega} &= a_{11} \omega + a_{22} r + b_1 \sigma_n + s_2, \\
\dot{r} &= a_{21} \omega + a_{22} r + b_2 \sigma_n + s_3.
\end{align*}
\]

Set the state vector is \( x(t) = [e, \phi, \omega, r]^T \), the control input signal is \( u(t) = \sigma_f \) and the external disturbance \( \omega(t) = [s_1, -\rho(\delta_c) v_x, s_2, s_3]^T \). Finally, the physical state space model of AGV is expressed as follows:

\[
\dot{x}(t) = A x(t) + B u(t) + \omega(t),
\]

where

\[
A = \begin{bmatrix}
0 & v_x & v_x & 0 \\
0 & 0 & 0 & 0 \\
0 & 0 & -\frac{C_n + C_m}{m^2 v_x^2} & -(1 + \frac{1}{l_m C_n + l_m C_m}) \\
0 & 0 & \frac{l_m C_n + l_m C_m}{I_x} & -\frac{l_m^2 C_n + l_m^2 C_m}{v_x I_x}
\end{bmatrix},
B = \begin{bmatrix}
0 \\
0 \\
0 \\
\frac{C_n}{m v_x^2} \\
\frac{l_m}{l_m C_n}
\end{bmatrix}.
\]

The experimental setup was conducted on the Simulink joint platform to verify the effectiveness of the proposed control algorithm in this paper using the data provided in reference [19]. The physical meanings of the parameters were defined in [19]. Specifically, \( h \) represents the distance from the front wheel to the center of gravity, and \( C_n \) and \( C_m \) denote the cornering stiffness of the front and rear tires, respectively. We set the intensity to 0.4. This comparison clearly demonstrates the superior performance of the proposed algorithm in dealing with system delays and DoS attacks. The impact of DoS attacks on system performance is further examined. We set \( h_M = 0 \) and \( \rho = 0.5 \). To evaluate the impact of varying \( h_M \) on the system, we used the Yalmip toolbox to solve for the maximum acceptable time delay \( \tau_{max} \).

### Table 2. The maximum acceptable time delay \( \tau_{max} \) under different preset sampling periods \( h \)

<table>
<thead>
<tr>
<th>( h )</th>
<th>Preset sampling periods</th>
</tr>
</thead>
<tbody>
<tr>
<td>0.2</td>
<td>1.7963</td>
</tr>
<tr>
<td>0.4</td>
<td>1.3821</td>
</tr>
<tr>
<td>0.6</td>
<td>1.1725</td>
</tr>
<tr>
<td>0.8</td>
<td>0.9974</td>
</tr>
<tr>
<td>1.0</td>
<td>0.5104</td>
</tr>
</tbody>
</table>

As shown in Table 2, the proposed control algorithm in this paper has a maximum acceptable delay limit of 1.3821 when \( h_M = 0.4 \). In contrast, reference [19] limits the maximum acceptable latency to \( \tau_{max} = 0.04 \). This comparison clearly demonstrates the superior performance of the proposed algorithm in dealing with system delays and DoS attacks. The impact of DoS attacks on system performance is further studied, and we conduct simulations with different attack strengths and maximum delay constraints. Specifically, we set \( h_M = 0.2 \) and examined the maximum acceptable delay of the DoS attack system under different attack strengths. The results are presented in Table 3, where we observe that the maximum acceptable time delay of the system changes with varying attack strengths. Notably, when the attack strength is set to \( G = 10 \), the maximum transmission time delay of the system is \( \tau_{max} = 0.5963 \). These results indicate the importance of implementing robust control strategies in NCSs that can handle and mitigate the effects of attacks, especially high-intensity DoS attacks. The proposed control algorithm in this paper has a computational complexity of \( 6n^2 + n \), which means that the system’s asymptotic stability can be ensured even with a low number of decision variables. Moreover, the low computational complexity of the control algorithm reduces processing time and energy consumption, making it more feasible for real-time control applications. In summary, the proposed control algorithm not only guarantees the system’s stability and security but also provides practical benefits by minimizing the computational burden and optimizing resource allocation.

### Table 3. The maximum acceptable time delay \( \tau_{max} \) under different DoS attack strength

<table>
<thead>
<tr>
<th>DoS attacks</th>
<th>Preset attack strength</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>1</td>
</tr>
<tr>
<td>( \tau_{max} )</td>
<td>2.3097</td>
</tr>
</tbody>
</table>
Then, the control gain matrix $K = 10^4 \times [2.0171 -1.9720 -0.9823 -0.6937]$ obtained using the method in Theorem 2 when the parameters $\mu_1$ and $\mu_2$ were set to 1. This control gain matrix was then used in a Simulink joint platform simulation experiment to verify the feasibility of the proposed control design method. The results presented in Figure 4 and Figure 5 demonstrate that the proposed control design method is effective in mitigating the impact of DoS attacks on the system, as the system can still converge smoothly under the designed controller and control algorithm, even when subjected to DoS attacks with high intensity and a short attack period. Furthermore, the study found that the proposed control design method is more effective than the method presented in [19], as it enables the system to tolerate a higher maximum delay limit under DoS attacks, as shown in Table 2. These results provide valuable insights into the development of robust control algorithms for NCSs that are vulnerable to DoS attacks, highlighting the importance of implementing such algorithms to ensure system stability and security. Additionally, the proposed control algorithm has relatively low computational complexity, making it a practical solution for real-time control applications.

**Figure 4.** System parameter state trajectory response with DoS attacks.

**Figure 5.** System parameter state trajectory response without DoS attacks.

Furthermore, selecting appropriate trigger thresholds is crucial for mitigating DoS attacks in practice. In this paper, we propose a novel approach based on GDA for optimizing trigger thresholds. By formulating the threshold selection as a constrained optimization problem, we can find optimal thresholds that minimize the trigger rate of legitimate traffic while maintaining high mitigation of DoS attacks. First, we
iterate through the $\rho_k$ values using the Python toolbox and then bring the results into the Yalmip toolbox for solving. This learning algorithm significantly improves resource efficiency by iteratively searching for a suitable value of $\rho_k$. The intelligent trigger threshold search mechanism employs machine learning to find the optimal threshold, denoted by $\rho$, by iteratively traversing the range $[0, 1]$ as shown in the sequence $\rho_1 \rightarrow \cdots \rightarrow \rho_2 \rightarrow \cdots \rightarrow \rho_{k-1} \rightarrow \cdots \rightarrow \rho_k \rightarrow \cdots$. In this way, the algorithm iteratively learns and searches for the $\rho^k$ with the lowest trigger rate. Additionally, we present the number of system triggers under GDA and traditional algorithms in Figures 6 and 7, respectively. Our results show that GDA-optimized thresholds can significantly reduce the number of false triggers compared to the conventional method, resulting in a lower trigger rate of 86.62% for GDA versus 88.5% for the traditional algorithm. These findings demonstrate the effectiveness of our proposed approach in reducing the impact of DoS attacks on network performance.

![Graph showing release instants and time intervals under GDA.](image)

**Figure 6.** Release instants and time intervals under GDA.

Finally, the optimized trigger thresholds can also provide additional benefits in terms of resource allocation and system resilience. By reducing the number of false triggers, our approach can free up more resources for other tasks or mitigate the impact of DoS attacks on system performance. In a word, our approach can enhance the security and reliability of network systems in the face of increasingly sophisticated DoS attacks.

![Graph showing release instants and time intervals under regular algorithm.](image)

**Figure 7.** Release instants and time intervals under regular algorithm.
5 Conclusion

This paper addressed the issue of NCSs under DoS attacks with periodicity and attack intensity. The research on the power of the DoS attacks was significant for establishing suitable defense mechanisms. The paper presented a method to construct appropriate LKFs, reducing the constraints of basic conditions and mitigating criterion conservatism. Additionally, the paper transformed the selection problem of the trigger threshold into an optimization problem with constraints and used the GDA to optimize the threshold, saving sampling resources. An ISETC was designed to ensure the normal operation of AGVs under DoS attacks. Finally, the proposed method’s effectiveness was verified by simulating the AGVs system based on the Simulink platform. In the future, further research could focus on developing more sophisticated defense mechanisms to protect NCSs from different types of cyber-attacks and enhancing the performance and robustness of AGVs systems under various adverse conditions.

Conflict of Interest

No conflict of interest exits in the submission of this manuscript, and the manuscript is approved by all authors for publication. I would like to declare on behalf of my co-authors that the work described was original research that has not been published previously, and not under consideration for publication elsewhere, in whole or in part. All the authors listed have approved the manuscript that is enclosed.

Authors' Contributions

Xiao Cai and Yuanlun Xie contributed to the conception of the study; Xiao Cai performed the experiment the data analyses and wrote the manuscript; Kaibo Shi contributed significantly to analysis and manuscript preparation; Kun She contributed significantly to the methodology and presentation of the manuscript; Shouming Zhong helped perform the analysis with constructive discussions.

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References

Xiao Cai et al.: Title Suppressed Due to Excessive Length


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