Output-Feedback Security Tracking for Robotic Systems Against DoS Attacks Using Finite-Time Observers

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ABSTRACT

This paper studies output-feedback security tracking control for robotic systems under denial-of-service (DoS) attacks, unknown nonlinearities, and external disturbances. A finite-time state observer based on radial basis function neural networks (RBFNNs) is developed to reconstruct unmeasured states and approximate the lumped uncertainty from output measurements. An adaptive nonlinear filter is then introduced to attenuate disturbance effects and approximation errors, and an output-feedback security controller is synthesized using observer and filter signals. Lyapunov analysis shows that, under an average dwell-time condition on DoS intervals, all closed-loop signals remain bounded, the tracking error is uniformly ultimately bounded, and the state estimates converge in finite time. Comparative simulations on a nonlinear unmanned marine system show consistent improvements in tracking accuracy, disturbance rejection, and resilience to packet dropouts.

KEYWORDS

Robotic systems; security tracking control; finite-time observation; RBF neural networks; adaptive nonlinear filtering; DoS attacks

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1 INTRODUCTION

Output tracking with partially or fully unmeasured states arises in many control applications. A wide range of motion control platforms, including robotic manipulators, unmanned aerial vehicles, and unmanned marine vessels, can be cast into networked second-order nonlinear forms [3]. When such systems communicate over networks, they are exposed to packet dropouts [39], quantization effects [21], time delays [24], and, most critically, malicious attacks [6, 8]. Network attacks may severely deteriorate performance or even destabilize the closed loop, which has motivated extensive research on security control over the past decade.

Among typical attack patterns, deception, false-data injection, and denial-of-service (DoS) are frequently studied [15, 29]. Recent years have seen comprehensive results for cyber-physical systems [19, 22, 25, 31] and, in particular, for networked nonlinear plants. For example, resilient model-free iterative learning control was developed to achieve output tracking under DoS and measurement fading [35]. State approximation and transmission management against DoS were addressed by multi-observer and resilient event-triggered designs in [18, 34]. For uncertain nonlinear dynamics under DoS, H_∞ tracking and filtering were investigated via probabilistic and event-triggered strategies [17, 32]. Asymptotic stabilization was studied using adaptive event-based fast terminal sliding-mode control and quantized linearization [14, 26]. Observer-based adaptive control coping with DoS together with deception/replay attacks was reported in [30]. Security of nonlinear complex networks and multi-agent systems under DoS was also examined in [13, 16, 33, 36].

Many of the above results assume Lipschitz-type nonlinearities [33, 35] or known smooth mappings [13, 36]. To broaden applicability, neural-network and fuzzy-logic models have been adopted, leading to observation and control schemes, often linear matrix inequality (LMI)-based, that handle unknown nonlinearities [1, 9, 28, 37]. However, these observers typically do not guarantee *finite-time* recovery of unmeasured states. Moreover, anti-attack mechanisms may introduce estimation/approximation errors that, if not properly compensated, degrade the closed-loop performance. Therefore, achieving finite-time state estimation while mitigating the perturbations induced by anti-attack designs remains a key challenge.

Disturbance rejection is another essential aspect. Secure control methods that jointly consider disturbances and DoS have emerged, e.g., adaptive observer-based fuzzy consensus for multi-agent systems [38]. In that line, the considered disturbance is state-dependent and vanishes as the state approaches zero. H_∞ performance via

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LMIs under external disturbances was studied in [27], yet disturbance effects were not explicitly compensated. Extended-state-observer-based designs were explored in [4] but rely on Bernoulli DoS assumptions. Norm-bounded disturbances were analyzed in [7], where the residual error scales with the disturbance magnitude and disturbance mitigation was not fully addressed.

Filtering is commonly employed in backstepping-type secure designs to avoid repeated differentiation [1, 9, 28, 37]. Nevertheless, existing *linear* filters underuse their potential for perturbation rejection. Adaptive *nonlinear* filters exploiting derivatives of the input and measured states were proposed in [10, 12] to enhance rejection capability, but the need for accurate derivative information renders the design conservative. This motivates new filters with strong anti-perturbation properties that do not rely on precise derivatives.

Motivated by these gaps, this paper tackles two issues: (i) constructing *finite-time* observers that estimate unavailable states from output measurements; (ii) developing anti-attack and perturbation-rejection control with reduced conservatism. We study output-feedback security tracking for disturbed second-order nonlinear systems under DoS. A radial-basis-function neural network (RBFNN) finite-time observer is employed to reconstruct the states and approximate unknown dynamics. Adaptive nonlinear compensation filters are designed within a backstepping framework to supply auxiliary signals that attenuate disturbances and RBFNN approximation errors. Controller parameters are selected via a set of LMIs to further reduce conservatism. Combining observer and filter outputs, an RBFNN-based security controller is derived to ensure bounded closed-loop signals and accurate tracking, which is validated by comparative simulations.

The main contributions are threefold. (I) We develop RBFNN-based *finite-time* observation strategies that estimate unmeasured states for a class of disturbed second-order nonlinear systems, extending beyond Lipschitz or known smooth cases [13, 33, 35, 36]. (II) We propose adaptive *nonlinear* compensation filters that strengthen steady-state behavior by suppressing perturbations, relaxing disturbance assumptions compared with [7, 38] and going beyond linear filters in [1, 9, 28, 37]. (III) By integrating observation and filtering signals, we design output-feedback security tracking controllers that simultaneously address perturbation rejection and anti-attack objectives with less conservative tuning.

The remainder of the paper is organized as follows. Section 2 formulates the problem. Section 3 presents the adaptive observer and the nonlinear filtering-based security control design. Section 4 reports comparative simulations. Section 5 concludes the paper.

2 PRELIMINARIES

2.1 Notations

Given a vector $\eta = [\eta_1, \eta_2, \ldots, \eta_m]^T$ and a constant $\varsigma > 0$, define $\mathrm{sig}^{\varsigma}(\eta) = \left[\mathrm{sgn}(\eta_1)|\eta_1|^{\varsigma}, \ldots, \mathrm{sgn}(\eta_m)|\eta_m|^{\varsigma}\right]^T$ and $\mathrm{sgn}(\eta) = [\mathrm{sgn}(\eta_1), \ldots, \mathrm{sgn}(\eta_m)]^T$, where $\mathrm{sgn}(\cdot)$ is the sign function. The notation $\mathrm{diag}(\eta)$ denotes a diagonal matrix with diagonal entries $\eta_1, \ldots, \eta_m$. The Kronecker product of $G \in R^{m\times n}$ and $W \in R^{p\times q}$ is written as $G \otimes W$.

2.2 Dynamics of Robotic Systems

For a broad class of robotic motion-control platforms, the disturbed standard second-order model is written as

$$\dot{\alpha}(t) = \beta(t), \tag{1a}$$

$$\dot{\beta}(t) = g\big(\alpha(t), \beta(t), t\big) + r\big(\alpha(t)\big)\big(u(t) + d(t)\big), \tag{1b}$$

$$y(t) = \alpha(t), \tag{1c}$$

where $\{\alpha(t), \beta(t)\} \in R^m$ denote position and velocity states, $y(t) \in R^m$ is the measured output, and $u(t) \in R^m$ is the control input. The unknown nonlinear mapping $g(\cdot) \in R^m$ aggregates plant uncertainties, $r(\alpha)$ is a bounded input gain, and the exogenous disturbance $d(t)$ satisfies $\|d(t)\| \le \bar{d}$ for some unknown constant $\bar{d} > 0$. Only the position $y = \alpha$ is measurable.

DoS model. Let $\{q_j\}_{j\in N}$ be the DoS starting instants and $Q_j := [q_j, q_j + \tau_j)$ the jth attack interval. Define the active/sleeping sets $H(\tau, t) := \cup_{j\in N} Q_j \cap [\tau, t]$ and $\Delta(\tau, t) := [\tau, t] \setminus H(\tau, t)$. The available measurement is $y^a = 0$ if $t \in H(0, \infty)$ and $y^a = y$ if $t \in \Delta(0, \infty)$. Following [23], the DoS duration is constrained by

$$|H(\tau, t)| \le \iota + \frac{t - \tau}{T}, \tag{2}$$

with $\iota \ge 0$, $T \ge 1$, and the DoS frequency satisfies

$$n(\tau, t) \le \varsigma + \frac{t - \tau}{\tau_d}, \tag{3}$$

with $\varsigma \ge 0$, $\tau_d > 0$.

2.3 Radial Basis Function Neural Networks

Following [2], an RBFNN is written as

$$\Re(\xi) = W^T \Psi(\xi), \tag{4}$$

and is used to approximate the unknown term $g(\cdot)$ in (1). Let $\xi := [\alpha^T, \beta^T]^T$ and $\hat{\xi} := [\alpha^T, \hat{\beta}^T]^T$. The approximation is

$$\hat{g}(\hat{\xi}) = \hat{W}^T \Psi(\hat{\xi}), \tag{5}$$

where $\Psi(\cdot)$ is the basis vector and $\hat{W}$ is the adaptive weight. Define the optimal weight

$$W^* := \arg\min_{\hat{W}} \left\|\hat{g}(\hat{\xi}) - g(\xi)\right\|. \tag{6}$$

Introduce the minimum approximation error $\iota(t)$ and the estimation error $\vartheta(t)$:

$$\iota(t) = g(\xi) - \hat{g}(\hat{\xi}|W^*), \tag{7a}$$

$$\vartheta(t) = g(\xi) - \hat{g}(\hat{\xi}|\hat{W}), \tag{7b}$$

which satisfy $\|\iota(t)\| \le \bar{\iota}$ and $\|\vartheta(t)\| \le \bar{\vartheta}$ for some positive constants $\bar{\iota}, \bar{\vartheta}$. Moreover, the activation satisfies $\|\Psi(\cdot)\| \le \bar{\Psi}$ with a constant $\bar{\Psi} > 0$.

2.4 Finite-Time Stability

Consider the nonlinear system

$$\dot{z}(t) = f(z(t)), \quad f(0) = 0, \tag{8}$$

where $z \in R^n$ and $f(\cdot)$ is continuous. Assume a unique forward solution exists for any initial condition.

Lemma 1. *[11] Suppose there exists a C^1 positive-definite function $V(z)$ such that*

$$\dot{V}(z) \le -\alpha V(z) - \beta V^b(z) + \iota, \tag{9}$$

where $\alpha > 0$, $\beta > 0$, $0 < b < 1$, and $\iota > 0$. Then $z(t)$ is finite-time stable and the settling time satisfies

$$T(z) \le \frac{1}{\alpha(1-b)} \ln \frac{\alpha V^{1-b}(z_0) + \beta}{\beta}, \tag{10}$$

where $V(z_0)$ is the initial value. Moreover, the convergence region is

$$\Delta = \left\{ z \,\middle|\, V(z) \le \min\left\{ \tfrac{2\iota}{\alpha}, (\tfrac{2\iota}{\alpha})^{1/b} \right\} \right\}. \tag{11}$$

2.5 Main Objective

Let $y_r(t)$ be the reference trajectory and define

$$x_1(t) = y(t) - y_r(t). \tag{12}$$

The goal is to ensure uniformly ultimately bounded tracking for the robotic system (1) under disturbances, unknown nonlinearities, and DoS attacks, and to drive $x_1(t)$ into a small neighborhood of the origin. To this end, two designs are pursued: (i) construct an effective RBFNN-based finite-time observation strategy to recover unmeasured states from output signals; (ii) develop an adaptive output-feedback security tracking controller, together with a filtering technique, to compensate the effects of disturbances, nonlinearities, and DoS attacks.

3 RBFNN-BASED OBSERVATION AND BACKSTEPPING TRACKING CONTROL DESIGNS

3.1 RBFNN-Based Observer

Consider the robotic model (1). We design

$$\dot{\hat{\alpha}} = \hat{\beta} + \Omega_\alpha^\rho, \tag{13a}$$

$$\dot{\hat{\beta}} = u + \hat{g}(\hat{\xi}) + \Omega_\beta^\rho, \tag{13b}$$

where $\hat{\xi} = [\hat{\alpha}^T, \hat{\beta}^T]^T$, and $\hat{g}(\hat{\xi}) = \hat{W}^T \Psi(\hat{\xi})$ is the RBFNN approximation of the lumped unknown dynamics in $\dot{\beta}$ (Sec. 2); $\rho = 0$ on $H(0,\infty)$ (DoS active case) and $\rho = 1$ on $\Delta(0,\infty)$ (DoS sleep case).

Define the estimation errors and an auxiliary signal as

$$e = \begin{bmatrix} e_\alpha \\ e_\beta \end{bmatrix} = \begin{bmatrix} \hat{\alpha} - \alpha \\ \hat{\beta} - \beta \end{bmatrix}, \quad \epsilon_\alpha = \begin{cases} \hat{\alpha} - \alpha, & t \in \Delta(0,\infty) \\ \hat{\alpha}, & t \in H(0,\infty) \end{cases},$$
$$\check{\alpha} = \begin{cases} \alpha, & t \in \Delta(0,\infty) \\ \hat{\alpha}, & t \in H(0,\infty). \end{cases} \tag{14}$$

Case $\rho = 0$ (DoS active). Choose $\Omega_\alpha^0 = K_\alpha^0 \epsilon_\alpha$, $\Omega_\beta^0 = K_\beta^0 \epsilon_\alpha$, set

$$\mathcal{A} = \begin{bmatrix} 0 & I_m \\ 0 & 0 \end{bmatrix} \otimes I_m, \qquad K^0 = \begin{bmatrix} (K_\alpha^0)^T & (K_\beta^0)^T \end{bmatrix}^T,$$

and denote by ϑ the NN approximation error and by ϖ the disturbance in (1). Then

$$\dot{e} = \mathcal{A} e + K^0 \epsilon_\alpha - \vartheta - \varpi. \tag{15}$$

Consider $V_0 = \frac{1}{2} e^T P^0 e$ with $P^0 = P^{0T} > 0$. Using Young's inequality gives

$$\begin{aligned} \dot{V}_0 =& \tfrac{1}{2} e^T (P^0 \mathcal{A} + \mathcal{A}^T P^0) e + e^T P^0 K^0 \epsilon_\alpha - e^T P^0 (\vartheta + \varpi) \\ \le& \tfrac{1}{2} e^T \Big(P^0 \mathcal{A} + \mathcal{A}^T P^0 + 2 P^0 K^0 I_1 + l_2 P^0 K^0 K^{0T} P^0 + 2 l_1 P^{0^2} \Big) e \\ &+ \bar{\iota} + \tfrac{1}{2 l_2} \|\alpha\|^2, \end{aligned}$$

where $l_1, l_2 > 0$, $I_1 = [I_m \ 0] \in \mathbb{R}^{m \times 2m}$, and $\bar{\iota} = \frac{1}{2 l_1} (\|\bar{\vartheta}\|^2 + \|\bar{\varpi}\|^2)$.

Case $\rho = 1$ (DoS sleep). Use the finite-time corrections

$$\Omega_\alpha^1 = -k_\alpha \, \xi_\alpha(e_\alpha), \tag{16a}$$

$$\Omega_\beta^1 = -k_\beta \, \xi_\beta(e_\alpha), \tag{16b}$$

with $0.8 < h < 1$, $\xi_\alpha = \mu_\alpha \operatorname{sig}^{\frac{3h-2}{h}}(e_\alpha) + \mu_\beta e_\alpha$, and

$$\xi_\beta = \tfrac{3h-2}{h} \mu_\alpha^2 \operatorname{sig}^{\frac{5h-4}{h}}(e_\alpha) + \tfrac{4h-2}{h} \mu_\alpha \mu_\beta \operatorname{sig}^{\frac{3h-2}{h}}(e_\alpha) + \mu_\beta^2 e_\alpha,$$

where $\mu_\alpha, \mu_\beta, k_\alpha, k_\beta > 0$. Let

$$\zeta = \begin{bmatrix} \xi_\alpha \\ e_\beta \end{bmatrix}, \quad A_m = \begin{bmatrix} -k_\alpha I_m & I_m \\ -k_\beta I_m & 0 \end{bmatrix}, \quad B_m = \operatorname{diag}(I_m, I_m),$$

and $\Lambda = \operatorname{diag}\big(|e_{\alpha,1}|^{\frac{2h-2}{h}}, \ldots, |e_{\alpha,m}|^{\frac{2h-2}{h}} \big)$. Then from (13)–(16),

$$\dot{\zeta} = \tfrac{3h-2}{h} \mu_\alpha (\Lambda \otimes I_2) A_m \zeta + \mu_\beta A_m \zeta - B_m (\vartheta + \varpi). \tag{17}$$

Proposition 1. *Suppose there exist $P^1 = P^{1T} > 0$ and $Q = Q^T > 0$ such that*

$$P^1 A_m + A_m^T P^1 + Q < 0, \qquad P^1 A_m + A_m^T P^1 + 2 l_1 \mu_\beta^{-1} P^1 B_m B_m^T P^1 < 0, \tag{18}$$

with $l_1 > 0$. Then e_α, e_β converge to small neighborhoods of the origin in finite time.

Proof. Choose $\bar{V}_0 = \frac{1}{2} \zeta^T P^1 \zeta$. From (17),

$$\begin{aligned} \dot{\bar{V}}_0 =& \frac{3h-2}{2h} \mu_\alpha \, \zeta^T \Big((\Lambda \otimes I_2) P^1 A_m + A_m^T P^1 (\Lambda \otimes I_2) \Big) \zeta \\ &+ \frac{1}{2} \mu_\beta \, \zeta^T \Big(P^1 A_m + A_m^T P^1 \Big) \zeta - \zeta^T P^1 B_m (\vartheta + \varpi). \end{aligned} \tag{19}$$

Using $P^1 A_m + A_m^T P^1 \le -Q$ (first inequality in (18)) and Young's inequality yields

$$\begin{aligned} \dot{\bar{V}}_0 \le& -\frac{3h-2}{2h} \mu_\alpha \, \zeta^T (\Lambda \otimes Q) \zeta - \frac{1}{2} \mu_\beta \, \zeta^T Q \zeta \\ &+ l_1 \, \zeta^T P^1 B_m B_m^T P^1 \zeta + \frac{1}{2 l_1} \Big(\|\bar{\vartheta}\|^2 + \|\bar{\varpi}\|^2 \Big). \end{aligned} \tag{20}$$

Since $\|e_\alpha\| \le \|\zeta\| / \mu_\beta$, we have $\|e_\alpha\|^{\frac{2h-2}{h}} \ge \mu_\beta^{\frac{2-2h}{h}} \|\zeta\|^{\frac{2h-2}{h}}$ and hence

$$\zeta^T (\Lambda \otimes Q) \zeta \ge \lambda_{\min}(Q) \, \mu_\beta^{\frac{2-2h}{h}} \|\zeta\|^{\frac{4h-2}{h}}.$$

Using the second inequality in (18), we obtain

$$\begin{aligned} \dot{\bar{V}}_0 \le& -\underbrace{\frac{3h-2}{2h} \mu_\alpha \, \mu_\beta^{\frac{2-2h}{h}} \lambda_{\min}(Q)}_{:=\beta_0} \|\zeta\|^{\frac{4h-2}{h}} \\ &- \underbrace{\Big(\tfrac{1}{2} \mu_\beta \lambda_{\min}(Q) - l_1 \lambda_{\max}(P^1 B_m B_m^T P^1) \Big)}_{:=\alpha_0} \|\zeta\|^2 + \bar{\iota}. \end{aligned} \tag{21}$$

Noting $\bar{V}_0 \ge \frac{1}{2} \lambda_{\min}(P^1) \|\zeta\|^2$ and

$$\bar{V}_0^{\frac{2h-1}{h}} \le \lambda_{\max}(P^1)^{\frac{2h-1}{h}} \|\zeta\|^{\frac{4h-2}{h}} / 2^{\frac{2h-1}{h}},$$

we infer

$$\dot{\bar{V}}_0 \le -\alpha_0' \bar{V}_0 - \beta_0' \bar{V}_0^{\frac{2h-1}{h}} + \bar{\iota}, \tag{22}$$

for some $\alpha_0', \beta_0' > 0$ explicitly determined by $(P^1, Q, \mu_\alpha, \mu_\beta)$. By Lemma 1, ζ converges in finite time to a compact set, hence so do e_α, e_β. □

3.2 Backstepping Tracking Control

Introduce

$$x_1 = \alpha - y_r, \qquad x_2 = \hat{\beta} - \theta_2, \qquad z_2 = \theta_2 - \alpha_1, \tag{23}$$

where α_1 is a differentiable virtual control and θ_2 is an adaptive nonlinear filter:

$$\dot{\theta}_2 = -\frac{1}{\rho_2}\theta_2 + \frac{1}{\rho_2}\alpha_1 - \beta_{12} z_2 \frac{\|z_2\|^2 \hat{k}_{12} + \hat{k}_{22} + \|z_2\|\|\dot{\alpha}_1^*\| + \frac{\xi}{2l_2}\|\check{\alpha}\|^2 + \Phi_2}{\|z_2\|^2 + \beta_{22}},$$

with $\Phi_2 = \frac{\mu}{2\gamma_{22}}\hat{k}_{22}^2$, $\rho_2 > 0$, $\beta_{12} > 1$, $\beta_{22} > 0$, $\xi > 1$. The adaptive laws are

$$\dot{\hat{k}}_{12} = \begin{cases} \gamma_{12}(\|z_2\|^2 - \lambda_{12}\hat{k}_{12}), & \|z_2\| \ge \sqrt{\frac{\beta_{22}}{\beta_{12}-1}}, \\ 0, & \text{otherwise}, \end{cases} \tag{24a}$$

$$\dot{\hat{k}}_{22} = \begin{cases} \gamma_{22}, & \|z_2\| \ge \sqrt{\frac{\beta_{22}}{\beta_{12}-1}}, \\ 0, & \text{otherwise}, \end{cases} \tag{24b}$$

with $\gamma_{12}, \gamma_{22}, \lambda_{12} > 0$.

Step 1. From (1) and (23), we have

$$\dot{x}_1 = \beta - \dot{y}_r = \hat{\beta} - e_\beta - \dot{y}_r = x_2 + z_2 + \alpha_1 - e_\beta - \dot{y}_r.$$

Choose

$$\alpha_1 = -(\beta_1 + 1)x_1^* + \dot{y}_r, \qquad x_1^* = \check{\alpha} - y_r,\ \beta_1 > 1. \tag{25}$$

Let $V_1 = \frac{1}{2}x_1^T x_1 + V_0$. Using (16) and Young's inequality,

$$\dot{V}_1 \le \tfrac{1}{2}e^T \Upsilon_0 e + \tfrac{1-\beta_1}{2}\|x_1\|^2 + \|x_2\|^2 + \|z_2\|^2 + \bar{\iota} + \phi_1, \tag{26}$$

where

$$\Upsilon_0 = P^0\mathcal{A} + \mathcal{A}^T P^0 + 2P^0K^0I_1 + l_2P^0K^0K^{0T}P^0 + 2l_1{P^0}^2 + 2I_2^T I_2$$

and $I_2 = [0\ I_m]$, while ϕ_1 collects the constant bounds from $\|\alpha\|^2$ terms.

Step 2. On $H(0,\infty)$, $\dot{x}_2 = u + \hat{g}(\hat{\xi}) + \Omega_\beta^0 - \dot{\theta}_2$. Augment V_1 by $\bar{V}_2 = \frac{1}{2}x_2^T x_2 + \frac{1}{2}z_2^T z_2 + \frac{1}{2\gamma_{12}}\tilde{k}_{12}^2 + \frac{1}{2\gamma_{22}}\tilde{k}_{22}^2$ to form $V_2 = V_1 + \bar{V}_2$, and choose

$$u = -(\beta_2 + \tfrac{3}{2})x_2 - \hat{g}(\hat{\xi}) - \Omega_\beta^0 + \dot{\theta}_2, \qquad \beta_2 > 0. \tag{27}$$

Assume $\|\dot{\alpha}_1\| \le \chi_{21}\|z_2\| + \chi_{22}$ for some unknown constants $\chi_{21}, \chi_{22} > 0$ (due to (25)), and take $\rho_2 = \frac{2}{2+\mu}$. Then, by direct differentiation and completing the squares,

$$\dot{V}_2 \le \tfrac{1}{2}e^T\big(\Upsilon_0 + (3+\bar{\beta})I_1^T I_1\big)e + \tfrac{1-\beta_1}{2}\|x_1\|^2 - \beta_2\|x_2\|^2 - \tfrac{\mu}{2}\|z_2\|^2 - \tfrac{\lambda_{12}}{2}\tilde{k}_{12}^2 - \frac{\mu}{2\gamma_{22}}\hat{k}_{22}^2 + \varphi_2, \tag{28}$$

where $\bar{\beta} > 0$ is a tuning scalar and φ_2 lumps bounded constants from the NN/disturbance terms via $\bar{\iota}$. On $\Delta(0,\infty)$, by Proposition 1 we have $\dot{\bar{V}}_0 \le -\alpha_0'\bar{V}_0 - \beta_0'\bar{V}_0^{\frac{2h-1}{h}} + \bar{\iota}$; combining with the same (α_1, θ_2, u) yields an inequality of the form (28) with the e-dependent part replaced by negative terms in $\bar{V}_0$.

3.3 LMI Computation and Main Results

To compute the observer gains and certify (16)–(28), solve

$$P^0\mathcal{A} + \mathcal{A}^T P^0 + 2P^0K^0I_1 + l_2P^0K^0K^{0T}P^0 + 2l_1{P^0}^2 + 2I_2^T I_2 + (3+\bar{\beta})I_1^T I_1 \le \nu P^0, \tag{29}$$

$$P^1A_m + A_m^T P^1 + 2l_1\mu_\beta^{-1}P^1B_mB_m^TP^1 + 2\mu_\beta^{-1}I_2^T I_2 \le -\mu P^1, \tag{30}$$

for some $\nu \ge \mu > 0$. By the Schur complement, these are equivalent to

$$\begin{bmatrix} \Upsilon_1 & * \\ \sqrt{2}\,P^0 & -\frac{1}{l_1}I \end{bmatrix} < 0, \qquad \begin{bmatrix} \Upsilon_2 & * \\ \sqrt{2}\,B_m^T P^1 & -\frac{\mu_\beta}{l_1}I \end{bmatrix} < 0, \tag{31}$$

with $\Upsilon_1 = P^0\mathcal{A} + \mathcal{A}^T P^0 + 2P^0K^0I_1 - \nu P^0 + (3+\bar{\beta})I_1^T I_1 + 2I_2^T I_2$ and $\Upsilon_2 = P^1A_m + A_m^T P^1 + 2\mu_\beta^{-1}I_2^T I_2 + \mu P^1$.

Theorem 2. *Consider the system* (1) *under DoS described by* (2)–(3)*. Let the observer* (13)–(16)*, virtual control* (25)*, filter* (24) *with* (24)*, and input* (27) *be applied. If* (31) *holds for some* $\mu, \nu > 0$ *and there exists* γ^* *such that*

$$1 - \beta_1 < -\mu, \qquad -\beta_2 < -\tfrac{\mu}{2}, \qquad \frac{\mu - \gamma^*}{\mu + \nu} > \frac{1}{T}, \qquad \gamma^* > \frac{\ln\lambda}{\tau_d}, \tag{32}$$

with $\lambda \ge 1$*, then all closed-loop signals are uniformly ultimately bounded and* $y = \alpha$ *tracks* y_r *with a bounded steady-state error.*

Proof. On $H(0,\infty)$, (28) and (29) imply

$$\dot{V}_2 \le \nu V_0 + c_1 - \beta_2\|x_2\|^2 - \frac{\mu}{2}\|z_2\|^2,$$

for some constant $c_1 > 0$. On $\Delta(0,\infty)$, Proposition 1 and (30) yield $\dot{V}_2 \le -\mu V_0 + c_2$, $c_2 > 0$. Let $\sigma(t) = \nu$ on $H(0,\infty)$ and $\sigma(t) = -\mu$ on $\Delta(0,\infty)$. Repeating the standard dwell-time integration over $[0,t]$ and inserting (2)–(3), we obtain

$$V_2(t) \le \lambda^{n(0,t)} \exp\Big(-\mu|H(0,t)| + \nu|\Delta(0,t)|\Big) V_2(0) + (c_1 + c_2)\int_0^t \lambda^{n(\tau,t)} \exp\Big(-\mu|H(\tau,t)| + \nu|\Delta(\tau,t)|\Big)\, d\tau. \tag{33}$$

By (32) the exponent is strictly negative; hence

$$V_2(t) \le \lambda^{\varsigma}\Big[e^{-\kappa t}V_2(0) + \frac{c_1 + c_2}{\kappa}\big(1 - e^{-\kappa t}\big)\Big] \tag{34}$$

for some $\kappa > 0$, which proves uniform ultimate boundedness of V_2 and thus of $e_\alpha, e_\beta, x_1, x_2, z_2$. Consequently, x_1 is ultimately bounded and $y = \alpha$ tracks y_r with bounded error. □

The adaptive nonlinear filter (24) explicitly attenuates perturbations (disturbances and NN approximation errors), improving steady-state accuracy compared with linear filters. The LMIs (31) allow tuning l_1, l_2 to reduce conservatism without enlarging the error bounds.

4 NUMERICAL EXAMPLE

We validate the proposed observer-and-filter-based controller on an unmanned surface vessel (USV) under DoS and disturbances. Let the position and velocity states be

$$\alpha := (x_s, y_s, \psi_s)^T, \qquad \beta := (u_s, v_s, r_s)^T,$$

so $y = \alpha$. The 3-DOF model is [5]

$$\begin{cases} \dot{\alpha} = J(\psi)\,\beta, \\ M\dot{\beta} + C(\beta)\beta + D(\beta)\beta = \tau + \varpi, \end{cases} \tag{35}$$

where $\tau = [\tau_x, \tau_y, \tau_\psi]^T$ is the body-fixed input, $\varpi = [\varpi_x, \varpi_y, \varpi_\psi]^T$ is an unknown disturbance, and

$$J(\psi) = \begin{bmatrix} \cos\psi & -\sin\psi & 0 \\ \sin\psi & \cos\psi & 0 \\ 0 & 0 & 1 \end{bmatrix}.$$

Parameters follow [20]:

$$M = \begin{bmatrix} 25.8 & 0 & 0 \\ 0 & 33.8 & 1.0948 \\ 0 & 1.0948 & 2.76 \end{bmatrix}, \quad C = \begin{bmatrix} 0 & 0 & c_{13} \\ 0 & 0 & c_{23} \\ -c_{13} & -c_{23} & 0 \end{bmatrix},$$

$$D = \begin{bmatrix} d_{11} & 0 & 0 \\ 0 & d_{22} & 0 \\ 0 & 0 & d_{33} \end{bmatrix},$$

with

$$c_{13} = -33.8\,v_s - 1.098\,r_s, \quad c_{23} = 25.8\,u_s,$$
$$d_{11} = 0.7225 + 1.3274|u_s| + 5.8864u_s^2,$$
$$d_{22} = 0.8896 + 36.4728|v_s| + 0.805|r_s|,$$
$$d_{33} = 1.9 - 0.08|v_s| + 0.75|r_s|.$$

Setup. The reference signal is

$$y_r(t) = \begin{bmatrix} 2\sin(t)\ \text{m} \\ \cos(t)\ \text{m} \\ 0.3\ \text{rad} \end{bmatrix}.$$

The disturbance signal is selected as

$$\varpi(t) = \begin{bmatrix} 0.2\sin(t) \\ 0.5\cos(0.1t) \\ 0.3 \end{bmatrix}.$$

Observer/filter-controller parameters are: $k_\alpha = 5$, $k_\beta = 10$, $\nu = 6$, $\mu = 4$, $\beta_1 = 5.1$, $\beta_2 = 3$, $\xi = 1.5$, $\lambda = 580$, $l_1 = l_2 = 0.5$. Initial states: $\alpha(0) = [1.5, 1, 0.1]^T$, $\beta(0) = 0$. Adaptive/NN settings: $h = 0.9$, $\mu_\alpha = \mu_\beta = 40$, $\rho_2 = \frac{1}{3}$, $\gamma_{12} = \gamma_{22} = 0.1$, $r_{p,l} = 0.1$, $\lambda_{12} = 40$, $\eta_{v,l} = 40$, $\beta_{12} = 1.2$, $\beta_{22} = 0.01$. Number of neurons $L = 15$; centers uniformly in $[-2, 2] \times [-2, 2]$; width $d_l = 3$. Initial values: $\hat{k}_{12}(0) = \hat{k}_{22}(0) = 2.5$, $\hat{W}_{v,l}(0) = 0$. DoS windows:

$$H(0, t) = [6, 6.5] \cup [12, 12.8] \cup [22, 22.4] \cup [27, 27.6] \cup [35.1, 35.6]\ \text{s}.$$

Results. Figures 1–9 summarize the outcomes and comparative results. To complement the visual evidence, Table 1 reports three quantitative metrics against the baselines in [1, 37].

Figure 1 shows that $x_1(t)$ remains bounded and decays after each DoS burst. Figure 2 provides trajectory-level consistency with the reference motion in the 3-D space. Figure 3 indicates lower steady-state error for the proposed method under simultaneous DoS and disturbances compared with [1, 37]. Figures 4–5 confirm accurate finite-time observation of both position and velocity despite measurement dropouts. Figure 6 demonstrates convergence of x_2, z_2 (cf. (23)), consistent with the analysis. The control input (Figure 7) is smooth without chattering. Adaptive gains and NN weights remain bounded (Figures 8–9). Overall, the RBFNN-based finite-time observer combined with the adaptive nonlinear filter achieves bounded output tracking and improves steady-state accuracy over the baselines in [1, 37]. Table 1 summarizes three quantitative comparisons: root mean squared error (RMSE) on [0, 40] s, steady-state RMSE on [38, 40] s, and mean error on [1, 40] s, which further illustrates the superiority of our proposed method. These statistics are consistent with the visual trends in Figures 3–6: the proposed scheme suppresses burst-induced excursions more rapidly and maintains smaller residual tracking fluctuations in the late stage.

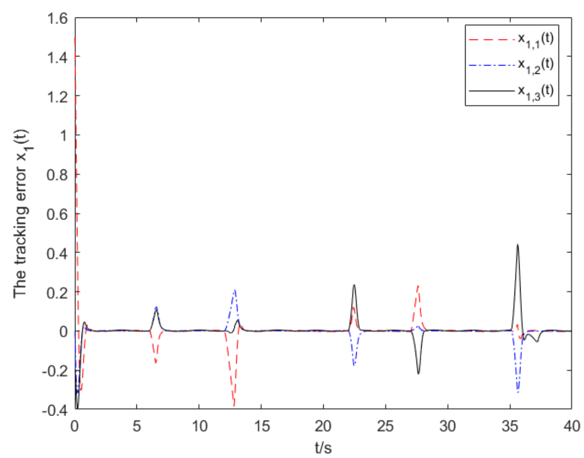

Figure 1: Tracking error $x_1(t) = \alpha(t) - y_r(t)$.

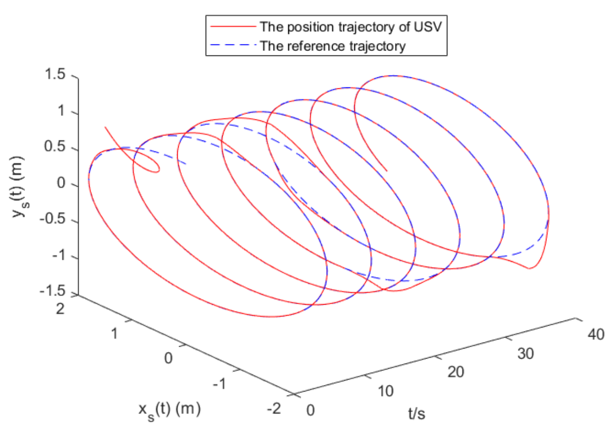

Figure 2: Position trajectory of the USV and reference trajectory in the 3-D space.

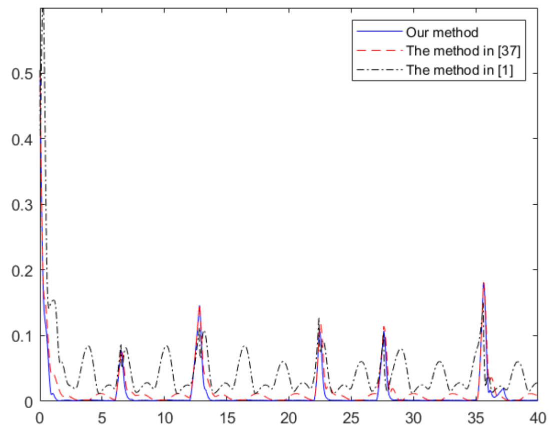

Figure 3: Error index $E(t) = \|x_1(t)\|/3$ (comparative).

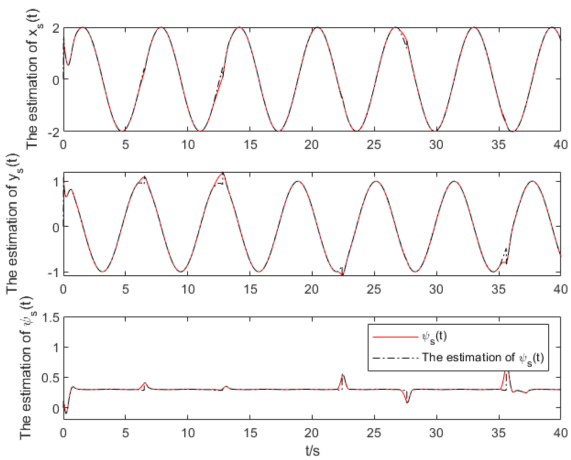

Figure 4: Position states: observer $\hat{\alpha}(t)$ vs. plant $\alpha(t)$.

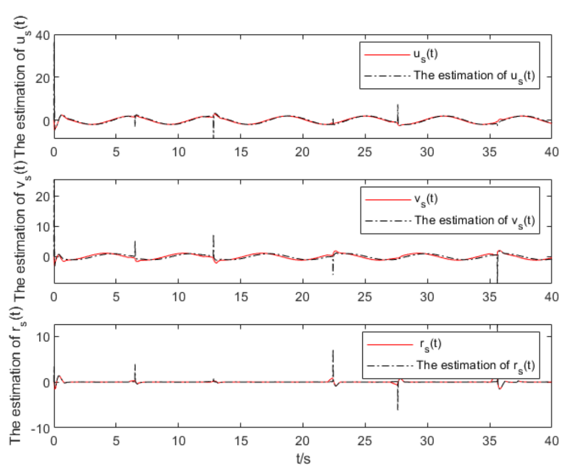

Figure 5: Velocity states: observer $\hat{\beta}(t)$ vs. plant $\beta(t)$.

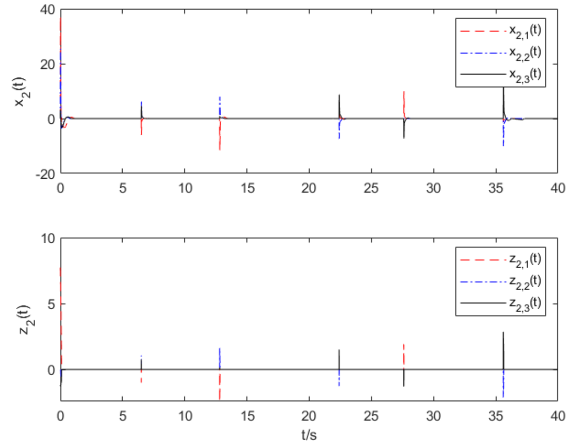

Figure 6: Auxiliary signals $x_2(t)$ and $z_2(t)$ in (23).

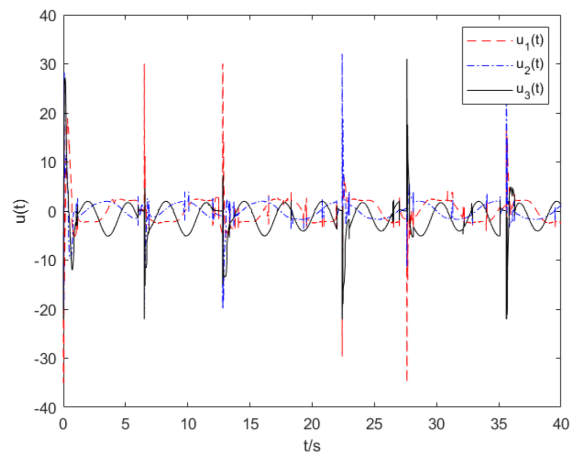

Figure 7: Control input $u = J(\psi)M^{-1}\tau(t)$.

Table 1: Quantitative comparison with two baselines.

Metric	Baseline A [1]	Baseline B [37]	Proposed	Improvement
RMSE of $E(t)$ on $[0, 40]$ s	0.2141	0.1772	0.1548	12.6%
Steady-state RMSE of $E(t)$ on $[38, 40]$ s	0.03760	0.007726	0.001114	85.6%
Mean $E(t)$ on $[1, 40]$ s	0.05326	0.04552	0.03262	28.3%

5 CONCLUSIONS

This work addressed output-feedback security tracking control for robotic (second-order nonlinear) systems subject to denial-of-service (DoS) attacks, unknown nonlinearities, and external disturbances. A finite-time RBFNN observer was designed to reconstruct unmeasured states and approximate the lumped uncertainty from output data. An adaptive nonlinear filter was then employed to

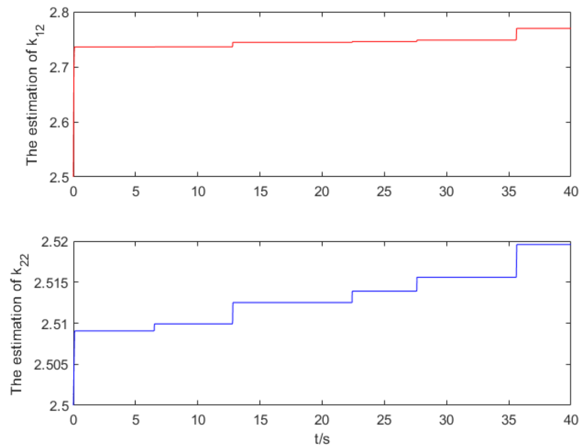

Figure 8: Adaptive estimates $\hat{k}_{12}(t)$ and $\hat{k}_{22}(t)$.

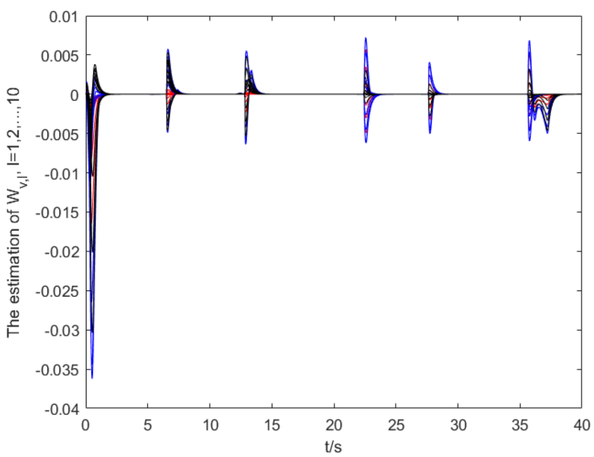

Figure 9: Estimated RBFNN weights (partial channels).

attenuate disturbance effects and approximation errors, and an output-feedback security controller was synthesized via backstepping using the observer and filter signals.

Lyapunov analysis established that, under an average dwell-time condition on the DoS intervals, all closed-loop signals are bounded and the tracking error is uniformly ultimately bounded, while the state estimates converge in finite time.

Comparative simulations on a nonlinear unmanned marine system corroborated the effectiveness of the method, showing lower tracking error and stronger disturbance rejection than the baselines in [1, 37], while maintaining resilience to packet dropouts. These results support combining finite-time RBFNN observation with adaptive nonlinear filtering for secure tracking in networked robotic systems.

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REFERENCES

[1] Liwei An and Guang-Hong Yang. 2019. Decentralized adaptive fuzzy secure control for nonlinear uncertain interconnected systems against intermittent DoS attacks. *IEEE Trans. Cybern.* 49, 3 (2019), 827–838.

[2] Martin D. Buhmann. 2003. *Radial Basis Functions: Theory and Implementations.* Cambridge University Press, Cambridge, UK.

[3] Paula Chanfreut, Jose M. Maestre, and Eduardo F. Camacho. 2021. A survey on clustering methods for distributed and networked control systems. *Annu. Rev. Control* 52 (2021), 75–90.

[4] Run-Ze Chen, Yuan-Xin Li, and Zhong-Sheng Hou. 2022. Distributed model-free adaptive control for multi-agent systems with external disturbances and DoS attacks. *Inf. Sci.* 613 (2022), 309–323.

[5] Thor I. Fossen, Kristin Y. Pettersen, and Roberto Galeazzi. 2015. Line-of-sight path following for Dubins paths with adaptive sideslip compensation of drift forces. *IEEE Trans. Control Syst. Technol.* 23, 2 (2015), 820–827.

[6] Weiming Fu, Jiahu Qin, Yang Shi, Wei Xing Zheng, and Yu Kang. 2020. Resilient consensus of discrete-time complex cyber-physical networks under deception attacks. *IEEE Trans. Ind. Informatics* 16, 7 (2020), 4868–4877.

[7] Wenmin He, Shi Li, Choon Ki Ahn, Jian Guo, and Zhengrong Xiang. 2022. Sampled-data stabilization of stochastic interconnected cyber-physical systems under DoS attacks. *IEEE Syst. J.* 16, 3 (2022), 3844–3854.

[8] Yabing Huang and Jun Zhao. 2021. Cyber-physical systems with multiple denial-of-service attackers: A game-theoretic framework. *IEEE Trans. Circuits Syst. I, Reg. Papers* 68, 10 (2021), 4349–4359.

[9] Xiaoyan Jiang, Xiaowu Mu, and Zenghui Hu. 2021. Decentralized adaptive fuzzy tracking control for a class of nonlinear uncertain interconnected systems with multiple faults and denial-of-service attack. *IEEE Trans. Fuzzy Syst.* 29, 10 (2021), 3130–3141.

[10] Xiaozheng Jin, Jing Chi, Jiahu Qin, Wei Xing Zheng, Xiaoming Wu, and Weiming Fu. 2026. Robust Security Control of a Class of Second-Order Nonlinear Systems Against DoS Attacks. *IEEE Trans. Syst. Man Cybern. Syst.* 56, 2 (2026), 1449–1463. https://doi.org/10.1109/TSMC.2025.3646685

[11] Xiaozheng Jin, Jiahuan Jiang, Jiahu Qin, Wei Xing Zheng, and Miaomiao Gao. 2025. Observer-Based Fixed-Time-Synchronized Control for Uncertain Euler-Lagrange Systems with Bias-Actuator Faults. *IEEE Trans. Cybern.* 55, 8 (2025), 3811–3824.

[12] Xiaozheng Jin, Shaoyu Lu, Jiahu Qin, Wei Xing Zheng, and Qingchen Liu. 2023. Adaptive ELM-based security control for a class of nonlinear interconnected systems with DoS attacks. *IEEE Trans. Cybern.* 53, 8 (2023), 5000–5012.

[13] Xiaozheng Jin, Shaoyu Lu, and Jiguo Yu. 2022. Adaptive NN-based consensus for a class of nonlinear multiagent systems with actuator faults and faulty networks. *IEEE Trans. Neural Netw. Learn. Syst.* 33, 8 (2022), 3474–3486.

[14] Rui Kato, Ahmet Cetinkaya, and Hideaki Ishii. 2022. Linearization-based quantized stabilization of nonlinear systems under DoS attacks. *IEEE Trans. Autom. Control* 67, 12 (2022), 6826–6833.

[15] Fanghui Li and Zhongsheng Hou. 2023. Distributed model-free adaptive control for MIMO nonlinear multiagent systems under deception attacks. *IEEE Trans. Syst. Man Cybern. Syst.* 53, 4 (2023), 2281–2291.

[16] Dan Liu and Dan Ye. 2020. Pinning-observer-based secure synchronization control for complex dynamical networks subject to DoS attacks. *IEEE Trans. Circuits Syst. I, Reg. Papers* 67, 12 (2020), 5394–5404.

[17] Jinliang Liu, Meng Yang, Xiangpeng Xie, Chen Peng, and Huaicheng Yan. 2020. Finite-time H_{infty} filtering for state-dependent uncertain systems with event-triggered mechanism and multiple attacks. *IEEE Trans. Circuits Syst. I, Reg. Papers* 67, 3 (2020), 1021–1034.

[18] Yan Liu and Guang-Hong Yang. 2022. Resilient event-triggered distributed state estimation for nonlinear systems against DoS attacks. *IEEE Trans. Cybern.* 52, 9 (2022), 9076–9089.

[19] An-Yang Lu and Guang-Hong Yang. 2023. Detection and identification of sparse sensor attacks in cyber-physical systems with side information. *IEEE Trans. Autom. Control* 68, 9 (2023), 5349–5364.

[20] Guanghao Lv, Zhouhua Peng, Haoliang Wang, Lu Liu, Dan Wang, and Tieshan Li. 2021. Extended-state-observer-based distributed model predictive formation control of under-actuated unmanned surface vehicles with collision avoidance. *Ocean Eng.* 238 (2021), 109587.

[21] Zepeng Ning, Xunyuan Yin, and Yang Shi. 2023. Quantization-uncertainty-dependent analysis and control of linear systems with multi-input-multi-output Quantization. *IEEE Trans. Circuits Syst. I, Reg. Papers* 70, 6 (2023), 2561–2572.

[22] Kunpeng Pan, Yang Lyu, and Quan Pan. 2022. Adaptive formation for multiagent systems subject to denial-of-service attacks. *IEEE Trans. Circuits Syst. I, Reg. Papers* 69, 8 (2022), 3391–3401.

[23] Claudio De Persis and Pietro Tesi. 2015. Input-to-state stabilizing control under denial-of-service. *IEEE Trans. Autom. Control* 60, 11 (2015), 2930–2944.

[24] Jiahu Qin and Huijun Gao. 2012. A sufficient condition for convergence of sampled-data consensus for double-integrator dynamics with nonuniform and time-varying communication delays. *IEEE Trans. Autom. Control* 57, 9 (2012), 2417–2422.

[25] Jiahu Qin, Menglin Li, Ling Shi, and Xinghuo Yu. 2018. Optimal denial-of-service attack scheduling with energy constraint over packet-dropping networks. *IEEE Trans. Autom. Control* 63, 6 (2018), 1648–1663.

[26] Mobin Saeedi, Jafar Zarei, Roozbeh Razavi-Far, and Mehrdad Saif. 2022. Event-triggered adaptive optimal fast terminal sliding mode control under denial-of-service attacks. *IEEE Syst. J.* 16, 2 (2022), 2684–2692.

[27] N. Sakthivel, M. Mounika Devi, and Guisheng Zhai. 2023. Non-fragile control for consensus of nonlinear multiagent systems under periodic denial of service attacks. *J. Franklin Inst.* 360 (2023), 2702–2728.

[28] Xinfeng Shao and Dan Ye. 2021. Neural-network-based adaptive secure control for nonstrict-feedback nonlinear interconnected systems under DoS attacks. *Neurocomputing* 448 (2021), 263–275.

[29] Yiming Sun, Jinyong Yu, Xinghu Yu, and Huijun Gao. 2020. Decentralized adaptive event-triggered control for a class of uncertain systems with deception attacks and its application to electronic circuits. *IEEE Trans. Circuits Syst. I, Reg. Papers* 67, 12 (2020), 5405–5416.

[30] A.H. Tahoun and M. Arafa. 2022. Secure control design for nonlinear cyber-physical systems under DoS, replay, and deception cyber-attacks with multiple transmission channels. *ISA Trans.* 128 (2022), 294–308.

[31] Xin Wang, Ju H. Park, and Huaqing Li. 2023. Fuzzy secure event-triggered control for networked nonlinear systems under DoS and deception attacks. *IEEE Trans. Syst. Man Cybern. Syst.* 53, 7 (2023), 4165–4175.

[32] Bin Wei, Engang Tian, Tao Zhang, and Xia Zhao. 2021. Probabilistic-constrained H_{infty} tracking control for a class of stochastic nonlinear systems subject to DoS attacks and measurement outliers. *IEEE Trans. Circuits Syst. I, Reg. Papers* 68, 10 (2021), 4381–4392.

[33] Tong Wu, Jian Liu, Lei Xue, and Yongbao Wu. 2023. Fixed-time synchronization of multilayer complex networks under denial-of-service attacks. *IEEE Trans. Circuits Syst. II, Exp. Briefs* 70, 9 (2023), 3519–3523.

[34] Jing-Jing Yan and Guang-Hong Yang. 2023. Secure state estimation of nonlinear cyber-physical systems against DoS attacks: A multiobserver approach. *IEEE Trans. Cybern.* 53, 3 (2023), 1447–1459.

[35] Wei Yu, Rui Wang, Xuhui Bu, Zhongsheng Hou, and Zhonghua Wu. 2022. Resilient model-free adaptive iterative learning control for nonlinear systems under periodic DoS attacks via a fading channel. *IEEE Trans. Syst. Man Cybern. Syst.* 52, 7 (2022), 4117–4128.

[36] Dan Zhang, Chao Deng, and Gang Feng. 2023. Resilient cooperative output regulation for nonlinear multi-agent systems under DoS attacks. *IEEE Trans. Autom. Control* 68, 4 (2023), 2521–2528.

[37] Lili Zhang, Wei-Wei Che, Chao Deng, and Zheng-Guang Wu. 2023. Prescribed performance fuzzy resilient control for nonlinear systems under DoS attacks. *IEEE Trans. Syst. Man Cybern. Syst.* 53, 5 (2023), 3104–3116.

[38] Yanhui Zhang, Gang Wang, Jian Sun, Hongyi Li, and Wei He. 2023. Distributed observer-based adaptive fuzzy consensus of nonlinear multiagent systems under DoS attacks and output disturbance. *IEEE Trans. Cybern.* 53, 3 (2023), 1994–2004.

[39] Tianwei Zhou, Zhiqiang Zuo, Yijing Wang, and Hongchao Li. 2021. Synchronization of Lurie systems under limited network transmission capacity with quantization and one-step packet dropout: An active method. *IEEE Trans. Syst. Man Cybern. Syst.* 51, 8 (2021), 4920–4928.