

Received 20 December 2022, accepted 1 January 2023, date of publication 5 January 2023, date of current version 10 January 2023.

Digital Object Identifier 10.1109/ACCESS.2023.3234439

RESEARCH ARTICLE

Gradient-Descent-Based Learning Gain for Backstepping Controller and Disturbance Observer of Nonlinear Systems

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This work was supported in part by the Basic Science Research Program through the National Research Foundation of Korea (NRF) funded by the Ministry of Education under Grant 2021R1A6A1A03043144; in part by the Technology Innovation Program (Development of Integrated Minimal Risk Maneuver Technology for Fallback System During Autonomous Driving) through the Ministry of Trade, Industry and Energy (MOTIE), South Korea, under Grant 20014121; in part by the Development of Electromechanical Brake Booster System for High-Efficiency Regenerative Braking of Micro-Electric Vehicles and Light Vehicles through MOTIE under Grant 20020728; in part by NRF Grant through the Korean Government, Ministry of Science and ICT (MSIT), under Grant 2022R1F1A1075479; and in part by the U.S. Department of Energy, Office of Energy Efficiency and Renewable Energy, Solar Energy Technologies Office Program, under Contract DE-AC05-00OR22725.

ABSTRACT This paper proposes a gradient-descent-based learning (GL) gain for backstepping controller and disturbance observer (DOB) of nonlinear system. The proposed method consists of the GL gain update law, controller, and DOB. The GL gain update law is proposed to adapt the control gain and DOB gain according to the direction that minimizes the cost function. The mathematical analysis reveals that the GL gain always has a positive sign and upper bound. The controller is designed via a backstepping procedure to track the desired output with GL control gain. The DOB is designed to estimate the unknown external disturbance with the GL DOB gain. Because the control and DOB gains are simultaneously tuned to achieve improved performance, the time consumption for tuning can be reduced. In addition, the peaking phenomenon can be avoided initially by a small initial value of GL gains. The stability of the closed-loop system is guaranteed using the input-to-state stability property. The performance of the proposed method was validated via simulations and experiments using a DC motor.

INDEX TERMS Learning control, disturbance observer (DOB), gradient-descent, input-to-state stability (ISS).

I. INTRODUCTION

Significant attention concerning the control of nonlinear dynamics has been increasing because applications with nonlinear characteristics, such as energy, flight, robotic, and mechatronics systems, have increased [1], [2], [3], [4], [5], [6]. With the advancement of the nonlinear stability theory, various control techniques have been developed to improve the control performance for nonlinear systems [6], [7], [8],

[9], [10], [11], [12], [13]. Feedback linearization has been presented to remove nonlinear dynamics using feedback [6]. Sliding mode control methods have been developed to achieve robust stabilization in a finite time [7], [8]. Lyapunov redesign methods have been suggested to guarantee the stability of nonlinear systems [9]. Recursive backstepping techniques have been proposed to compensate for an uncertain disturbance that does not satisfy matching conditions [10], [11]. The disturbance observer (DOB)-based control methods have been developed to compensate for unknown external disturbances [12], [13], [14]. Further, neural-network-based

The associate editor coordinating the review of this manuscript and approving it for publication was Jesus Felez .

adaptive control algorithms have been proposed to achieve robustness against system uncertainties using a neural network to approximate unknown complex nonlinear dynamics [15], [16]. These methods improved control performance and robustness for various nonlinear applications.

Detailed guidelines for gain selection are unclear in terms of the implementation. Therefore, tuning the gain is an unavoidable and sometimes very time-consuming process. Generally, to achieve precise and robust control performance, high control gain is required [17], [18]. Likewise, a high observer gain is necessary to obtain precise estimation performance [13], [19]. However, a high gain may induce the peaking phenomenon due to the multiplication of the high gain and the initial error. The peaking phenomenon may make the finite time escape of system state, which can lead to system instability [19], [20], [27]. And the high gain in the controller and/or the observer may result in amplifying high frequency measurement noise.

Various gain-tuning methods have been proposed to determine the proper gain for the controller and observer [21], [22], [23], [24], [25], [26]. A proportional-integral-derivative (PID) gain self-tuning methods have been developed based on gradient-descent using sliding-mode dynamics [21]. A self-tuning PID with supervisory control based on the Lyapunov approach has been reported [22]. A variable PID tuning method has been proposed using the relationship between the PID and backstepping control [23]. In [25], a backstepping control gain-tuning method was designed to adjust for the desired transient performance using a combination of nominal and variation gain. Regarding the observer gain selection, the disturbance observer gain-tuning method was developed based on a cut-off frequency of the disturbance [26]. Although these methods intuitively resolved the gain-tuning problem, the mathematical analysis of the adaptive tuning gain for the desired performance is insufficient.

In this paper, the control problem in nonlinear systems with disturbance of the following strict-feedback canonical form is considered as follows:

$$\begin{aligned}\dot{x}_i &= f_i(\bar{x}_i) + g_i(\bar{x}_i)x_{i+1} + \omega_i, \quad i \in [1, \dots, n-1] \\ \dot{x}_n &= f_n(\bar{x}_n) + g_n(\bar{x}_n)u + \omega_n\end{aligned}\quad (1)$$

where $\bar{x}_i = [x_1, x_2, \dots, x_i]^T \in \mathbb{R}^i$ is state variables, $u \in \mathbb{R}$ denotes the system input, and $\omega_i \in \mathbb{R}$ represents the external disturbance. The proposed method consists of the gradient-descent-based learning (GL) gain update law, controller, and DOB. The GL gain update law is proposed to adapt the control and observer gain according to the direction that minimizes the cost function. The mathematical analysis reveals that the GL gain always has a positive sign and upper bound to guarantee stability. The controller is designed via a backstepping procedure to track the desired output for (1) with the GL control gain. The DOB is designed to estimate the unknown external disturbance with the GL DOB gain. The proposed method can avoid the peaking phenomenon using the GL gain and suppress the tracking error within the

desired bound. Control and DOB gain values are simultaneously tuned to achieve improved performance; thus, the time consumption for tuning can be reduced. The stability of the closed-loop system is guaranteed using the input-to-state stability (ISS) property. The performance of the proposed method is validated via simulations and experiments using a DC motor.

The main contributions are as follows:

- The GL gain update law is proposed to adapt the control and observer gain according to the direction that minimizes the cost function.
- The time consumption for tuning can be reduced to obtain satisfactory performance.
- The proposed method can avoid the peaking phenomenon and suppress the error within the desired bound.

II. GRADIENT-DESCENT BASED LEARNING GAIN

A GL gain is proposed to suppress the state within the desired upper bound. A simple example system is used for illustration purposes before designing the DOB and backstepping controller for (1). Stable first-order dynamics with a perturbation term [27] are considered:

$$\begin{aligned}\dot{e} &= -\hat{\lambda}e + \rho \\ &\leq -\hat{\lambda}e + \rho_{\max}\end{aligned}\quad (2)$$

where e denotes the state, $\hat{\lambda}$ represents the GL gain, ρ indicates the perturbation term, and $\rho_{\max}$ is the upper bound of the perturbation term (i.e., $\rho_{\max} = \sup_{0 \leq t \leq \infty} |\rho|$). Integrating (2) over $[0, t]$, the following solution can be obtained:

$$|e(t)| \leq e(0) \exp^{-\hat{\lambda}t} + \frac{\rho_{\max}}{\hat{\lambda}}. \quad (3)$$

Therefore, the state can not converge to zero but enters the bound, which is determined by the GL gain.

A. GL GAIN UPDATE LAW

Gradient descent is an optimization method to minimize the cost function [28], [29], [30]. When the cost function is convex, all local minima solutions become global minima solutions, and the cost function can converge to the global solution. Therefore, the selection of the cost function is important. The cost function [31] is proposed as follows:

$$\begin{aligned}C(\hat{\lambda}) &= \dot{e} + \Lambda(1 - \gamma)e \\ J(\hat{\lambda}) &= \frac{1}{2}C^2\end{aligned}\quad (4)$$

where γ is designed as follows:

$$\gamma = \begin{cases} 0, & |e| > \varepsilon \\ 1, & |e| \leq \varepsilon \end{cases} \quad (5)$$

where $\Lambda > 0$ is the weight constant for error, ε denotes a small positive constant for the magnitude of the desired

bound. In addition, $\Lambda(1 - \gamma)e$ in the cost function is eliminated using γ when the state enters the desired bound. The gradient-descent-based update rule is designed as follows:

$$\dot{\hat{\lambda}} = -\eta \frac{\partial J}{\partial \hat{\lambda}} \quad (6)$$

where η represents the running rate chosen as a positive constant. The partial derivative of the cost function can be obtained using the chain rule:

$$\frac{\partial J}{\partial \hat{\lambda}} = C \frac{\partial C}{\partial \hat{\lambda}} = C(-e). \quad (7)$$

Therefore, (6) can be rewritten as

$$\dot{\hat{\lambda}} = \eta C e. \quad (8)$$

The initial value is chosen as the positive constant, $\hat{\lambda}(0) > 0$. In addition, existence of $(1 - \gamma)$ does not affect the convexity of (4). To demonstrate the convexity of (4), the second derivative of the cost function, $\ddot{J}(\hat{\lambda})$, can be rewritten using chain rule as follows:

$$\begin{aligned} \frac{\partial^2 J}{\partial \hat{\lambda}^2} &= \frac{\partial}{\partial \hat{\lambda}} \left(C \frac{\partial C}{\partial \hat{\lambda}} \right) = (-e)(-e) \\ &= e^2 \geq 0. \end{aligned} \quad (9)$$

From (9), because the cost function is convex regardless of $(1 - \gamma)$, the cost function converges to the global minimum.

Theorem 1: We consider the stable first-order dynamics with perturbation (2). If the cost function and update rule are chosen by (4) and (8), the state is bounded by

$$\lim_{t \rightarrow \infty} |e(t)| \leq \varepsilon \quad (10)$$

after some time, T_b . Further, the GL gain always has a positive sign and upper bound to guarantee stability:

$$\hat{\lambda}_{\max} = \hat{\lambda}(0) + \frac{1}{2}\eta\varepsilon^2 + \eta\Lambda E^2 T_b \quad (11)$$

where $E = \sup_{0 \leq t \leq T_b} |e(t)|$.

◇

Proof: From (3), the upper bound of state is

$$|e(t)| \leq \frac{\rho_{\max}}{\hat{\lambda}}. \quad (12)$$

The magnitude of the GL gain determines the upper bound of the state. When $|e(t)| > \varepsilon$, and $\gamma = 0$, the GL gain can be obtained by integrating (8) as follows:

$$\begin{aligned} \hat{\lambda}(t) &= \int_0^t \eta C e d\tau \\ &= \hat{\lambda}(0) + \frac{1}{2}\eta e(t)^2 + \int_0^t \eta \Lambda e(\tau)^2 d\tau. \end{aligned} \quad (13)$$

Therefore, if the initial value of the gain is positive, the GL gain is always positive. Moreover, the GL gain is increased by the time integration of $\eta \Lambda e^2$. Simultaneously, the upper bound of the state is decreased as much as the increment of the GL gain until the upper bound of the state (12) is smaller than the desired bound, ε . Define some time T_b when $|e(t)| \leq \varepsilon$,

and $\gamma = 1$. After T_b , because the cost function is changed by γ , the GL gain can be obtained as follows:

$$\begin{aligned} \hat{\lambda}(t) &= \int_0^{T_b} \eta(\dot{e} + \Lambda(1 - \gamma)e) d\tau + \int_{T_b}^t \eta(\dot{e}) d\tau \\ &= \hat{\lambda}(0) + \frac{1}{2}\eta e(t)^2 + \int_0^{T_b} \eta \Lambda e(\tau)^2 d\tau. \end{aligned} \quad (14)$$

Therefore, because the time integration term has an upper bound, the GL gain also has an upper bound:

$$\begin{aligned} \hat{\lambda}(\infty) &\leq \hat{\lambda}(0) + \frac{1}{2}\eta\varepsilon^2 + \int_0^{T_b} \eta \Lambda E^2 d\tau \\ &\leq \hat{\lambda}(0) + \frac{1}{2}\eta\varepsilon^2 + \eta \Lambda E^2 T_b = \hat{\lambda}_{\max} \end{aligned} \quad (15)$$

where E is a constant that satisfies this condition, such that $E = \sup_{0 \leq t \leq T_b} |e(t)|$. ◇

Remark 1: The function of $(1 - \gamma)$ is essential to obtain the upper bound of the GL gain in the implementation aspect. The GL gain becomes infinity without $(1 - \gamma)$. By integrating (8) with cost function without $(1 - \gamma)$, the GL gain can be obtained as follows:

$$\begin{aligned} \hat{\lambda}(t) &= \int_0^t \eta C e d\tau \\ &= \hat{\lambda}(0) + \frac{1}{2}\eta e(t)^2 + \int_0^t \eta \Lambda e(\tau)^2 d\tau. \end{aligned} \quad (16)$$

Because the state can never converge to zero for various reasons, such as disturbances and noise, in practice, the GL gain is continually increased by the time integration of $\eta \Lambda e^2$. Therefore, the GL gain becomes $\hat{\lambda}(\infty) = \infty$. ◇

Remark 2: The purpose of the GL gain update law is different from the existing adaptive control method for parameter optimization. The GL gain is designed to obtain the control or DOB gain, which obtains the desired performance using gradient descent with a cost function based on closed-loop dynamics. The existing adaptive control method for parameter optimization is designed to overcome the parametric uncertainties of the system dynamics [10], [15], [16]. The proposed method can avoid the peaking phenomenon and suppress the tracking error within the desired bound using the GL gain. The control and DOB gains are simultaneously updated to achieve the desired performance; thus, the time consumption for tuning can be reduced in practice. ◇

III. DESIGN OF GRADIENT-DESCENT BASED DISTURBANCE OBSERVER

The disturbance observer is designed to estimate the disturbance for the system in (1) with the following assumption.

Assumption 1: : The sign of $g_i(x_i)$ is known, $|g_i(x_i)| > 0$, and an upper positive bound of $g_i(x_i)$ exist such that $\sup_{0 \leq t \leq \infty} |g_i(x_i)| = \bar{g}_i$ ◇

Assumption 2: A disturbance, ω_i , $i \in [1, \dots, n]$ and the derivative of disturbances, δ_i , $i \in [1, \dots, n]$ are

bounded. Therefore, an upper positive bound of $|\delta_i|$ such that $\sup_{0 \leq t \leq \infty} |\delta_i(t)| = \delta_{i \max}$. $\diamond$

The disturbances in (1) can be rewritten as follows:

$$\begin{aligned}\omega_i &= \dot{x}_i - f_i(\bar{x}_i) - g_i(\bar{x}_i)x_{i+1}, \quad 1 \leq i \leq n-1, \\ \omega_n &= \dot{x}_n - f_n(\bar{x}_n) - g_n(\bar{x}_n)u.\end{aligned}\quad (17)$$

The estimated disturbances, $\hat{\omega}_i$, $i \in [1, \dots, n]$ and estimation error of disturbances, $\tilde{\omega}_i$, $i \in [1, \dots, n]$, are defined as follows to design the DOB:

$$\tilde{\omega}_i = \omega_i - \hat{\omega}_i. \quad (18)$$

The disturbance observer [32] is designed as follows:

$$\begin{aligned}\hat{\omega}_i &= \hat{l}_i(x_i - \hat{x}_i), \quad i \in [1, \dots, n-1] \\ \dot{\hat{x}}_i &= f_i(\bar{x}_i) + g_i(\bar{x}_i)x_{i+1} + \hat{\omega}_i \\ \hat{\omega}_n &= \hat{l}_n(x_n - \hat{x}_n) \\ \dot{\hat{x}}_n &= f_n(\bar{x}_n) + g_n(\bar{x}_n)u + \hat{\omega}_n\end{aligned}\quad (19)$$

where $\hat{l}_i > 0$, $i \in [1, \dots, n]$ are the GL DOB gains. The dynamics of $\tilde{\omega}_i$ with (19) are obtained as follows:

$$\dot{\tilde{\omega}}_i = -\hat{l}_i \tilde{\omega}_i + \delta_i \quad (20)$$

where δ_i , $i \in [1, \dots, n]$ are derivative of the disturbances. The upper bound of the estimation error is determined for the GL DOB gain $\hat{l}_i$. In the frequency aspect, the transfer function ω_i to $\tilde{\omega}_i$ can be defined from (20) as a high-pass filter $H_i(s)$ with a cut-off frequency $\hat{l}_i$ as follows:

$$H_i(s) = \frac{\tilde{\Omega}_i(s)}{\Omega_i(s)} = \frac{s}{s + \hat{l}_i} \quad (21)$$

where s denotes the Laplace operator, $\tilde{\Omega}_i(s)$ and $\Omega_i(s)$ represent the Laplace transform of ω_i and $\tilde{\omega}_i$, respectively. Therefore, the DOB gain is designed by maximum frequency of disturbance. The maximum frequency of the disturbance is unknown and different for each case. Generally, the proper DOB gain is selected by trial and error. However, the GL gain can be resolved using this consumption process.

A. GL DOB GAIN UPDATE LAW

This section proposes the GL DOB gain to suppress the estimation error within the desired bound. Based on Theorem 1, the cost function is proposed as follows:

$$\begin{aligned}C_{di}(\hat{l}_i) &= \dot{\tilde{\omega}}_i + L_{di}(1 - \gamma_{di})\tilde{\omega}_i \\ J_{di}(\hat{l}_i) &= \frac{1}{2}C_{di}^2, \quad i \in [1, \dots, n]\end{aligned}\quad (22)$$

where γ_{di} is designed as follows:

$$\gamma_{di} = \begin{cases} 0, & |\tilde{\omega}_i| > \tilde{\omega}_{i \max}^d \\ 1, & |\tilde{\omega}_i| \leq \tilde{\omega}_{i \max}^d \end{cases} \quad (23)$$

where $L_{di} > 0$ represents the weight for the estimation error, and $\tilde{\omega}_{i \max}^d$ denotes a small positive constant as the magnitude

of the desired bound. From (6), the GL DOB gain update rule is designed as follows:

$$\dot{\hat{l}}_i = -\eta_{di} \frac{\partial J_{di}}{\partial \hat{l}_i} \quad (24)$$

where η_{di} is running rate which is chosen positive constant. Using similar manner in (7), (24) can be rewritten as

$$\dot{\hat{l}}_i = \eta_{di} C_{di} \tilde{\omega}_i. \quad (25)$$

The initial value is chosen as the positive constant, $\hat{l}_i(0) > 0$.

Corollary 1: From Theorem 1, we consider the disturbance estimation error dynamics (20). If the cost function and updated rule are chosen by (22) and (25), the disturbance estimation error is bounded by

$$\lim_{t \rightarrow \infty} |\tilde{\omega}_i(t)| \leq \tilde{\omega}_{i \max}^d \quad (26)$$

after T_{bi}^D , $i \in [1, \dots, n]$ when $|\tilde{\omega}(t)| \leq \tilde{\omega}_{i \max}^d$, and $\gamma_{di} = 1$. In addition, the GL DOB gains always have a positive sign and upper bound to guarantee the stability:

$$\hat{l}_{i \max} = \hat{l}_i(0) + \frac{1}{2}\eta_{di}(\tilde{\omega}_{i \max}^d)^2 + \eta_{di}L_{di}\Omega_i^2 T_{bi}^D \quad (27)$$

where $\Omega_i = \sup_{0 \leq t \leq T_{bi}^D} |\tilde{\omega}_i(t)|$. $\diamond$

IV. GRADIENT-DESCENT BASED CONTROL FOR STRICT-FEEDBACK SYSTEMS

The controller is designed for (1) using the backstepping technique. In addition, the GL control gain update law is proposed to suppress the tracking error within the desired upper bound. We define the tracking error variables as follows:

$$z_1 = x_i - x_{jd}, \quad j \in [1, \dots, n]. \quad (28)$$

The tracking error dynamics become

$$\begin{aligned}\dot{z}_i &= f_i(\bar{x}_i) + g_i(\bar{x}_i)(z_{i+1} + x_{i+1d}) + \omega_i - \dot{x}_{id}, \\ i &\in [1, \dots, n-1] \\ \dot{z}_n &= f_n(\bar{x}_n) + g_n(\bar{x}_n)u + \omega_n - \dot{x}_{nd}.\end{aligned}\quad (29)$$

We propose the following control laws:

$$\begin{aligned}x_{i+1d} &= \frac{1}{g_i(\bar{x}_i)}(\dot{x}_{id} - f_i(\bar{x}_i) - \hat{\omega}_i - \hat{k}_i z_i) \\ i &\in [1, \dots, n-1] \\ u &= \frac{1}{g_n(\bar{x}_n)}(\dot{x}_{nd} - f_n(\bar{x}_n) - \hat{\omega}_n - \hat{k}_n z_n).\end{aligned}\quad (30)$$

With the control law (30), the closed-loop tracking error dynamics (29) can be obtained as follows:

$$\begin{aligned}\dot{z}_i &= -\hat{k}_i z_i + g_i(\bar{x}_i)z_{i+1} + \tilde{\omega}_i, \quad i \in [1, \dots, n-1] \\ \dot{z}_n &= -\hat{k}_n z_n + \tilde{\omega}_n.\end{aligned}\quad (31)$$

Theorem 2: We consider the closed-loop tracking error system (29). By the control input in (30), the closed-loop

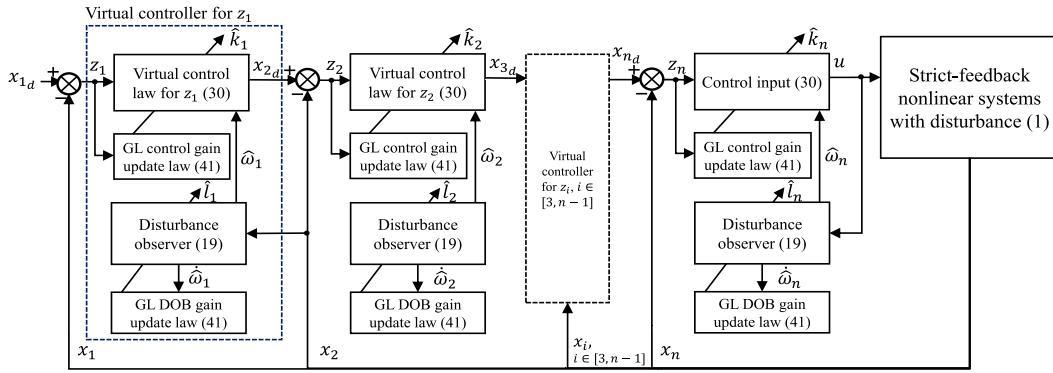


FIGURE 1. Block diagram of proposed method.

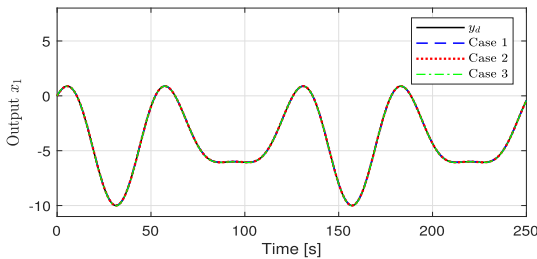


FIGURE 2. Simulation results: Control performance.

tracking error system is a serial interconnected ISS system with the following properties:

$$|z_i(t)| \leq \exp\left(-\frac{\hat{k}_i}{2}t\right) z_i(0) + \frac{2}{\hat{k}_i} \sup_{0 \leq \tau \leq t} \Delta_i(z_{i+1}(\tau)),$$

$$i \in [1, \dots, n-1]$$

$$|z_n(t)| \leq \exp\left(-\frac{\hat{k}_n}{2}t\right) z_n(0) + \frac{2}{\hat{k}_n} \sup_{0 \leq \tau \leq t} |\tilde{w}_n(\tau)| \quad (32)$$

where

$$\Delta_i(z_{i+1}(t)) = |\bar{g}_i| |z_{i+1}(t)| + |\tilde{w}_i(t)|. \quad (33)$$

Proof: By (31), the derivative of $\frac{z_i^2}{2}$ becomes

$$\frac{d}{dt} \left(\frac{z_i^2}{2} \right) = z_i \dot{z}_i$$

$$\leq -\hat{k}_i z_i^2 + |z_i| |\tilde{w}_i|$$

$$\leq -\frac{\hat{k}_i}{2} z_i^2 \quad \forall \quad |z_i(t)| \geq \frac{2}{\hat{k}_i} |\tilde{w}_i|. \quad (34)$$

Using [10], Th. C. 2], the result can be obtained:

$$|z_n(t)| \leq \exp\left(-\frac{\hat{k}_n}{2}t\right) z_n(0) + \frac{2}{\hat{k}_n} \sup_{0 \leq \tau \leq t} |\tilde{w}_n(\tau)|. \quad (35)$$

From (35), the relationship between z_n and $|\tilde{w}_n|$ satisfies the ISS property. Similarly, the derivative of $\frac{z_i^2}{2}$ can be obtained

as follows:

$$\frac{d}{dt} \left(\frac{z_i^2}{2} \right) = z_i \dot{z}_i$$

$$\leq -\hat{k}_i z_i^2 + |z_i| (|\bar{g}_i| |z_{i+1}| + |\tilde{w}_i|)$$

$$\leq -\frac{\hat{k}_i}{2} z_i^2 \quad \forall \quad |z_i| \geq \frac{2}{\hat{k}_i} \Delta_i. \quad (36)$$

Then

$$|z_i(t)| \leq \exp\left(-\frac{\hat{k}_i}{2}t\right) z_i(0) + \frac{2}{\hat{k}_i} \sup_{0 \leq \tau \leq t} \Delta_i(z_{i+1}(\tau)),$$

$$i \in [1, \dots, n-1]. \quad (37)$$

In addition, (37) indicates that the relationship between z_i and Δ_i has the ISS property. The boundedness of Δ_i is determined by $|z_{i+1}(t)|$ from (33), because $|\bar{g}_i|$ and $|\tilde{w}_i(t)|$ are bounded from the Assumption 1 and (20). Therefore, the ISS property between z_i and Δ_i is equivalent to the ISS property between z_i and z_{i+1} . From (35) and (37), the ISS property of the overall closed-loop system is represented by (32). Therefore, the closed-loop system in (31) is the serial interconnected system of the ISS system. $\diamond$

A. GL CONTROL GAIN UPDATE LAW

Based on Theorem 1, the cost function is selected for GL control gain as follows:

$$C_j(\hat{k}) = \dot{z}_j + K_j(1 - \gamma_j)z_j$$

$$J_j(\hat{k}) = \frac{1}{2} C_j^2 \quad (38)$$

where γ_j is designed as

$$\gamma_j = \begin{cases} 0, & |z_j| > \varepsilon_j \\ 1, & |z_j| \leq \varepsilon_j \end{cases} \quad (39)$$

where $K_j > 0$ denotes the weight for tracking error, ε_j is a small positive constant as the magnitude of the desired bound. The GL control gain update rule is designed as follows:

$$\dot{\hat{k}}_j = -\eta_j \frac{\partial J_j}{\partial \hat{k}_j} \quad (40)$$

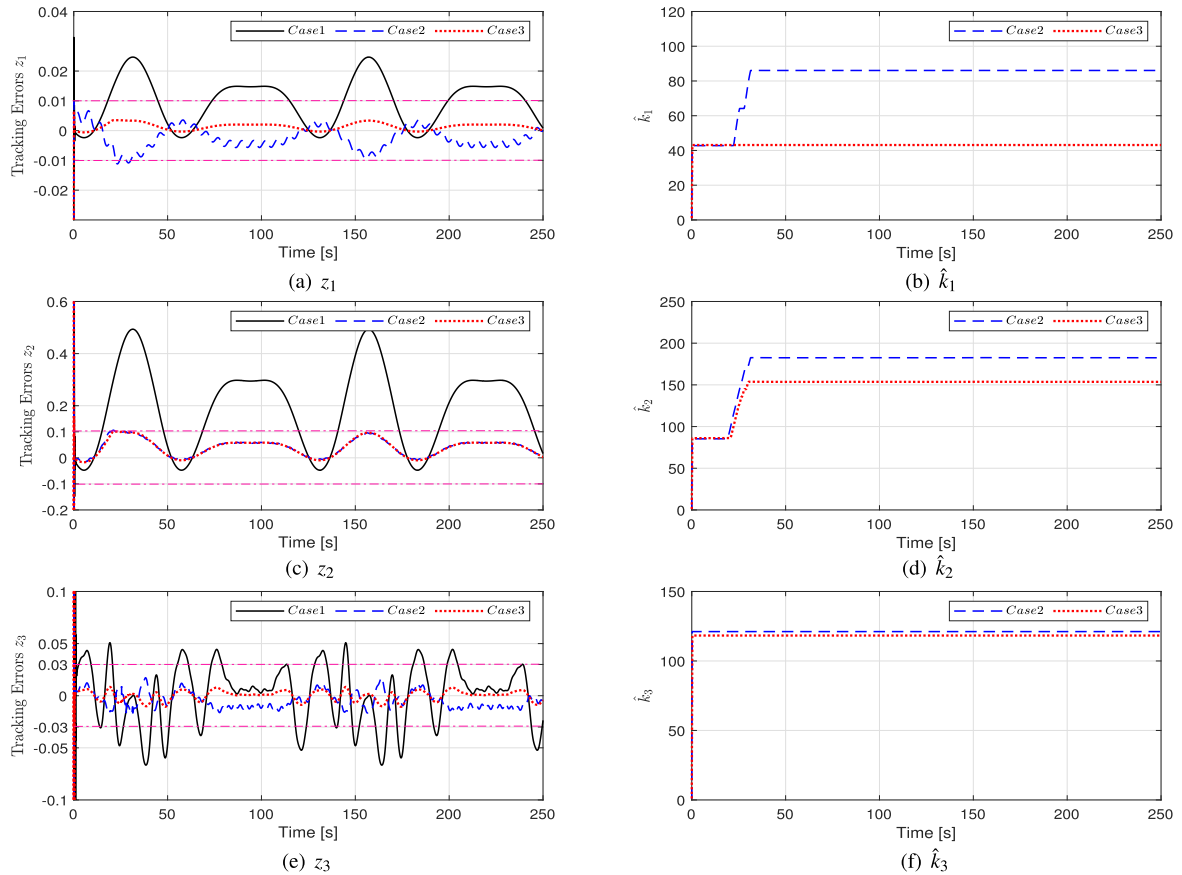


FIGURE 3. Simulation results: Tracking errors and GL control gain.

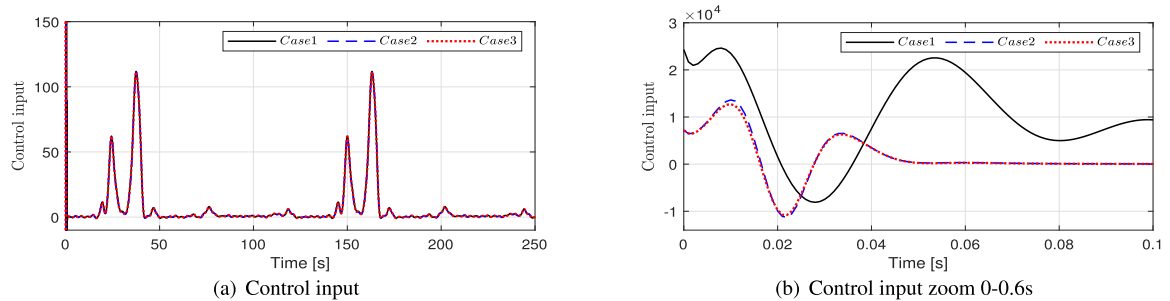


FIGURE 4. Simulation results: Control input.

where η_j indicates the running rate chosen as the positive constant. Similarly to (7), (40) can be rewritten as follows:

$$\dot{\hat{k}}_j = \eta_j C_j z_j. \quad (41)$$

The initial value is chosen as the positive constant, $\hat{k}_j(0) > 0$.

Corollary 2: From Theorem 1, we consider the tracking error dynamics (31). If the cost function and updated rule are chosen by (38) and (41), the tracking error is bounded by

$$\lim_{t \rightarrow \infty} |z_j| \leq \varepsilon_j \quad (42)$$

after T_{bj}^Z , $j \in [1, \dots, n]$ when $|z_j| \leq \varepsilon_j$, and $\gamma_j = 1$. In addition, the GL control gain always has a

positive sign and the upper bound to guarantee the stability:

$$\hat{k}_{j \max} = \hat{k}_j(0) + \frac{1}{2} \eta_j \varepsilon_j^2 + \eta_j K_j \kappa_j^2 T_{bj}^Z \quad (43)$$

where $\kappa_j = \sup_{0 \leq t \leq T_{bj}^Z} |z_j|$. $\diamond$

Fig. 1 presents a block diagram of the proposed method for indicating the details of the control procedure and signals. Each virtual controller for $z_i, i \in [1, n - 1]$ comprises a controller via backstepping with the GL control gain update law and DOB with the GL DOB gain update law.

Remark 3: Suggestions are provided to select the primary design parameters for the proposed method. In the GL gain update law, a large K_i and η_i help improve transient

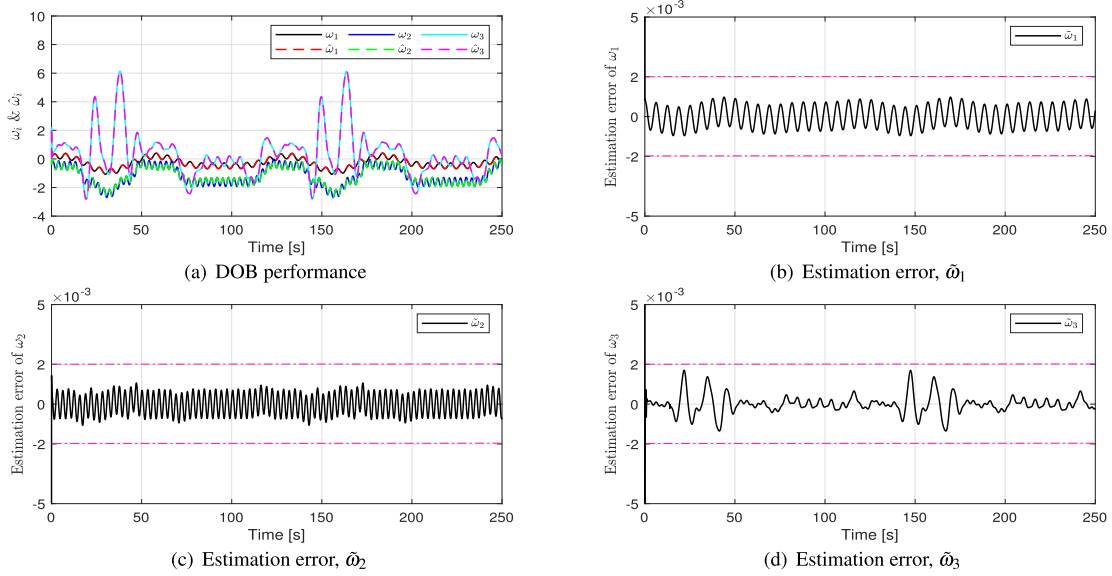


FIGURE 5. Simulation results: DOB performance and estimation error of Case 3.

performance because a GL gain rapidly can be varying. However, an excessively large value of C may induce an unnecessarily large variation; thus, the proper selection of K_i and η_i is recommended according to the scale of the tracking error for each state. Moreover, if the desired upper bound of the tracking error ϵ_i is too small, the GL gain may converge to an unnecessarily large control gain. Additionally, ϵ_i is also recommended according to the scale of the tracking error for each state. $\diamond$

Remark 4: A high control gain cannot be used initially because the peaking phenomenon occurs due to the multiplication of the high control gain and the initial error. However, the peaking phenomenon can be avoided in the GL gain at the outset because the initial values of the GL gains are selected as suitably small values. However, the minimal initial values of the GL gains may result in a poor transient response. Therefore, the initial values of the GL gains are selected by trial and error, considering both the transient response and peaking phenomenon. In addition, the GL gain is increased until the tracking error is sufficiently suppressed in the desired bound $|z_j| \leq \epsilon_j$. However, an increase in the GL gain does not affect the control input because the tracking error simultaneously decreases. $\diamond$

V. SIMULATION AND EXPERIMENTAL RESULTS

A. SIMULATION RESULTS

We consider the third-order system with disturbance presented in [33] as the example

$$\begin{aligned}\dot{x}_1 &= 2 \sin(x_1) + 1.5x_2 + \omega_1(x_1, t) \\ \dot{x}_2 &= 0.8x_1x_2 + x_3 + \omega_2(\bar{x}_2, t) \\ \dot{x}_3 &= -x_3^2 + 2u + \omega_3(\bar{x}_3, t)\end{aligned}\quad (44)$$

where

$$\omega_1(x_1, t) = 0.1 \sin(t) + 0.1x_1 + 0.12$$

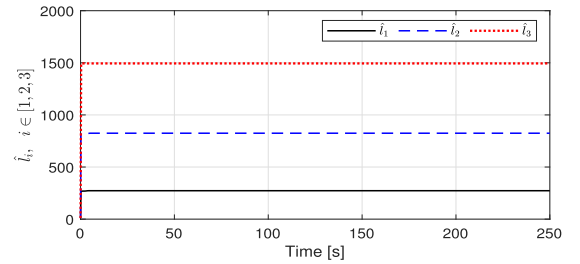


FIGURE 6. Simulation results: Gradient-descent based learning DOB gain of Case 3.

$$\omega_2(\bar{x}_2, t) = 0.3 \sin(2t) + 0.2x_1 + 0.2x_2 - 0.4$$

$$\omega_3(\bar{x}_3, t) = 0.2 \sin(2t) + 0.2x_1 + 0.3x_2 + 0.2x_3 + 0.3.$$

The desired output shown in Fig. 2 was used as follows:

$$x_{1d} = 2 \sin(0.15t) + 4 \cos(0.1t) - 3.9. \quad (45)$$

The DOBs (46) are designed as follows:

$$\begin{aligned}\hat{\omega}_1(x_1, t) &= \hat{l}_1(x_1 - \hat{x}_1) \\ \hat{x}_1(x_1, t) &= 2 \sin(x_1) + 1.5x_2 + \hat{\omega}_1(x_1, t) \\ \hat{\omega}_2(\bar{x}_2, t) &= \hat{l}_2(x_2 - \hat{x}_1) \\ \hat{x}_2(\bar{x}_2, t) &= 0.8x_1x_2 + x_3 + \hat{\omega}_2(\bar{x}_2, t) \\ \hat{\omega}_3(\bar{x}_3, t) &= \hat{l}_3(x_3 - \hat{x}_1) \\ \hat{x}_3(\bar{x}_3, t) &= -x_3^2 + 2u + \hat{\omega}_3(\bar{x}_3, t).\end{aligned}\quad (46)$$

The initial GL DOB gains, weights, and desired bound were selected as $\hat{l}_1(0) = 100$, $\hat{l}_2(0) = 10$, $\hat{l}_3(0) = 10$, $L_{di} = 2000$, $\eta_{di} = 1000$, and $\tilde{\omega}_{i\max}^d = 0.005$ $di \in [1, 2, 3]$. The tracking controller is designed as follows:

$$\begin{aligned}x_{2d} &= \frac{1}{1.5}(-2 \sin(x_1) - \hat{\omega}_1(x_1, t) + \dot{x}_{1d} - \hat{k}_1z_1) \\ x_{3d} &= -0.8x_1x_2 - \hat{\omega}_2(\bar{x}_2, t) + \dot{x}_{2d} - \hat{k}_2z_2\end{aligned}$$

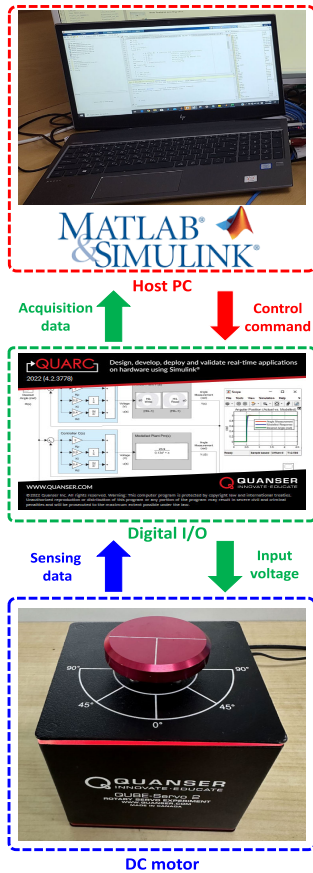


FIGURE 7. DC motor experimental testbed.

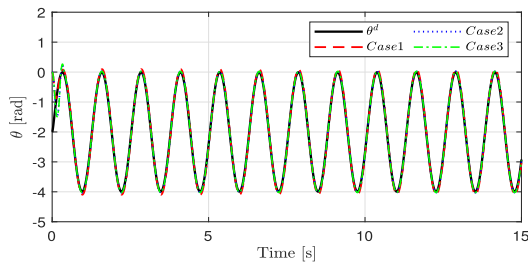


FIGURE 8. Experimental results: Control performance.

$$u = \frac{1}{2}(x_3^2 - \hat{\omega}_3(\bar{x}_3, t) + \dot{x}_{3d} - \hat{k}_3 z_3) \quad (47)$$

where $z_i = x_i - x_{id}$, $i \in [1, 2, 3]$.

Three cases were evaluated to assess the performance of the proposed method.

Case 1: [Constant gain backstepping control with GL DOB]

The controller (47) and DOB (46) are applied in Case 1. However, the constant control gains were selected as $k_1 = k_2 = k_3 = 30$. The control gains were selected by considering the peak at the initial input.

Case 2: [GL gain backstepping control without GL DOB]

As the disturbances are not compensated for, the estimated disturbances are set to zero such that $\hat{\omega}_i = 0$, $i \in [1, 2, 3]$ in (47). The initial control gains, and weights were set as

$\hat{k}_1(0) = \hat{k}_2(0) = \hat{k}_3(0) = 0.1$, $K_1 = \eta_1 = 250$, $K_2 = \eta_2 = 30$, and $K_3 = \eta_3 = 1$. The desired bounds were set as $\varepsilon_1 = 0.01$, $\varepsilon_2 = 0.1$, and $\varepsilon_3 = 0.03$.

Case 3: [GL gain backstepping control with GL DOB: proposed method]

The controller (47) and DOB (46) are applied in Case 3. The initial control gains, weights, and desired bound were selected the same as about Case 2.

The tracking control performance is illustrated in Fig. 2. In all cases, the output tracked the desired output trajectory well. The tracking errors and GL control gains are depicted in Fig. 3. The dashed-dotted line represents the desired upper bound of the error. The tracking error in Case 2 was lower than in Case 1. In Case 2, although the disturbances were not compensated for, the tracking errors were suppressed in the desired bound by the increased GL control gains. When the output tracking error, $|z_1|$, becomes larger than the desired upper bound at $t=25s$, in Fig. 3 (a), the GL control gain in Case 2 increased until $|z_1|$ was smaller than desired upper bound in Fig. 3 (b). In Case 3, as the disturbance was compensated for in control input (47), GL control gains were updated to a small value than in Case 2. The proposed method (Case 3) improved control performance as compared to Case 2. The control inputs of Cases 1 to 3 are presented in Fig. 4. Despite the control gains in Case 1 was selected by considering the peaking phenomenon, a higher peaking of input in Case 1 can be observed compared with Cases 2 and 3 at $t=0s$. Although the GL control gains become larger than the constant gain, the same effort of control input can be observed in all of cases in Fig. 4. Increased GL gain dose not affect the control input because the tracking error simultaneously decreases. The DOB performance and estimation error in Case 3 are presented in Fig. 5. The DOB estimated external disturbance well. The GL DOB gains of proposed method (Case 3) are displayed in Fig. 6. Likewise, the GL DOB gains are updated to suppress the estimation error within the desired bound. We can observe that the disturbance estimation performance was successfully suppressed in the desired bound by the increased GL DOB gains.

B. EXPERIMENTAL RESULTS

Experiments were conducted to validate the position tracking performance of the proposed method. A DC servo motor system manufactured by Quanser Corp. was used for the experiment. An incremental encoder with a resolution of 2048 pulses/revs was used. A host computer implemented the controller using MATLAB/Simulink and uploaded the executable output code to the QUARC real-time system. The control sampling rate was 1 kHz. Fig. 7 presents the experimental configuration of the DC motor testing set. DC motor dynamics can be expressed as

$$\begin{aligned} \dot{\theta} &= \omega \\ \dot{\omega} &= \frac{k_t}{J}i + \frac{1}{J}(-B\omega) \\ \dot{i} &= \frac{1}{L}(-k_b\omega - Ri + v) \end{aligned}$$

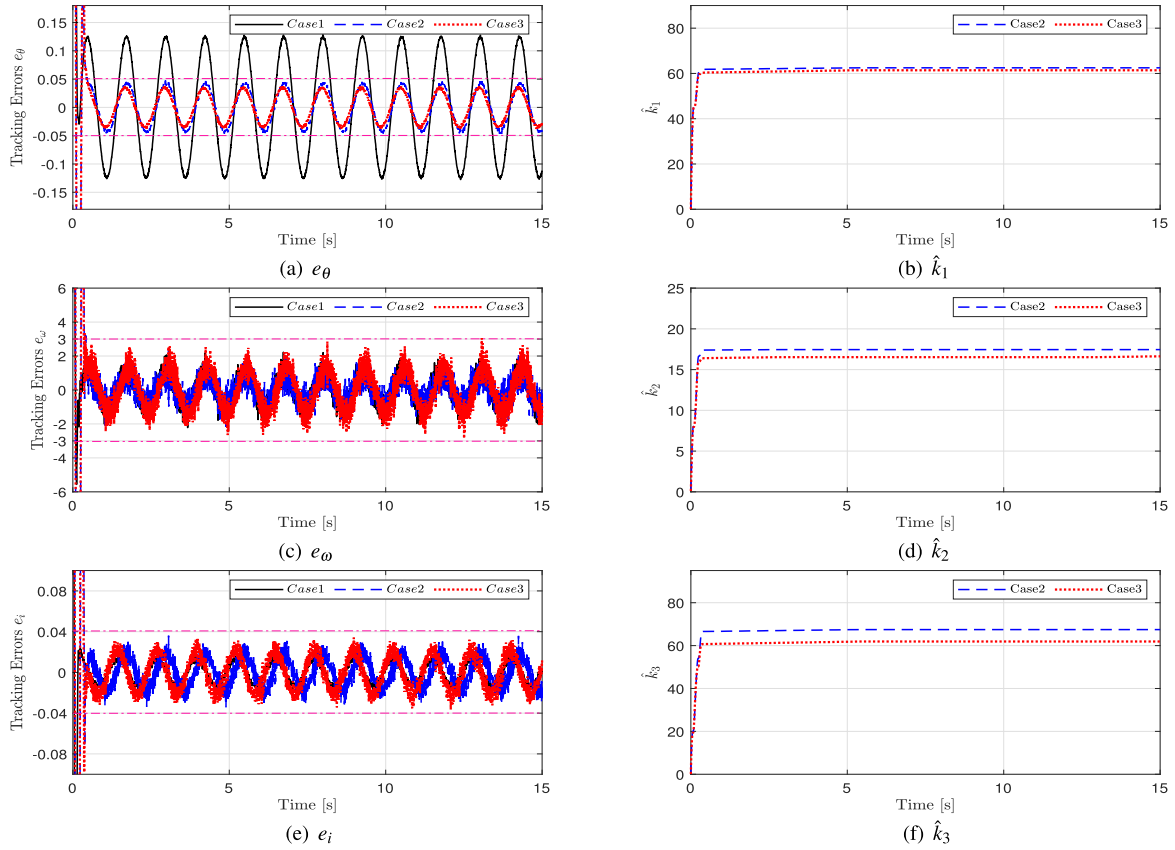


FIGURE 9. Experimental results: Tracking errors and GL gains.

where θ denotes the angular position [rad], ω represents the angular velocity [rad/s], i indicates the current [mA], v denotes the control input [V] $J = 2.09 \times 10^{-5}$ is inertia [kg·m²], $k_t = 0.042$ is torque constant [N·m/A], $L = 1.16 \times 10^{-3}$ is inductance [H], $k_b = 0.042$ is electromotive force constant [V·s/rad], $R = 8.4$ is resistance [Ω], and B is an unknown viscous friction coefficient. The tracing error variable, $e_x = x - x^d$, $x \in [\theta, \omega, i]$, and disturbance, $d_1 = -B\omega$, are defined. The desired position illustrated in Fig. 8 was used:

$$\theta^d = 2\sin\left(\frac{8\pi}{5}t\right) - 2 \quad (48)$$

The tracking controller are designed as follows:

$$\begin{aligned} \omega^d &= -\hat{k}_1 e_\theta + \dot{\theta}^d \\ i^d &= \frac{J}{k_t} \left(-\frac{1}{J} \hat{d}_1 - \hat{k}_2 e_\omega + \dot{\omega}^d \right) \\ v &= L \left(\frac{k_b}{L} \omega + \frac{R}{L} i - \hat{k}_3 e_i + L \dot{i}^d \right) \end{aligned} \quad (49)$$

The DOB are designed as follows:

$$\begin{aligned} \dot{\hat{d}}_1 &= \hat{l}_1 (J\omega - \hat{\omega}) \\ \dot{\hat{\omega}} &= k_t i + \hat{d}_1 \end{aligned} \quad (50)$$

The same GL DOB is applied to Cases 1 and 3. The initial GL DOB gains, weights, and desired bound were selected as $\hat{l}_1(0) = 10$, and $L_1 = \eta_1 = 10000$. The desired bound of the estimation error was set as $\tilde{\omega}_1^d = 1.5 \times 10^{-3}$.

The three cases were evaluated to assess the performance of the proposed method.

Case 1: [Constant gain backstepping control with GL DOB]

The controller (49) and DOB (50) are applied in Case 3. However, constant control gains were selected: $k_1 = 20$, $k_2 = 7$, and $k_3 = 60$. The control gains were selected by considering the peaking at the initial input.

Case 2: [GL gain backstepping control without GL DOB]

As the disturbances are not compensated for, the estimated disturbances were set to zero (e.g., $\hat{d}_1 = 0$ in (49)). The initial control gains, initial DOB gains, and design factors were set as $\hat{k}_1(0) = \hat{k}_2(0) = \hat{k}_3(0) = 0.1$, $K_1 = \eta_1 = 15$, $K_2 = \eta_2 = 0.2$, and $K_3 = \eta_3 = 30$ in Case 2. The desired bounds of tracking error were set as $\varepsilon_1 = 0.05$, $\varepsilon_2 = 3$, and $\varepsilon_3 = 0.04$.

Case 3: [GL gain backstepping control with GL DOB: proposed method]

The controller (49) and DOB (50) are applied in Case 3. The initial control gains, weights, and desired bound were selected the same as in Case 2.

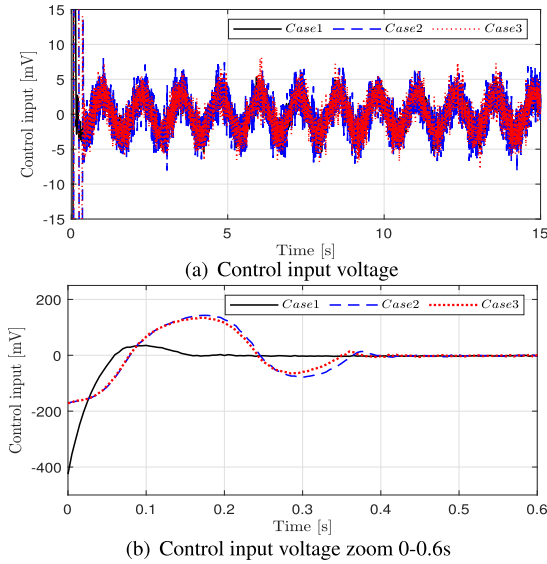


FIGURE 10. Experimental results: Control input.

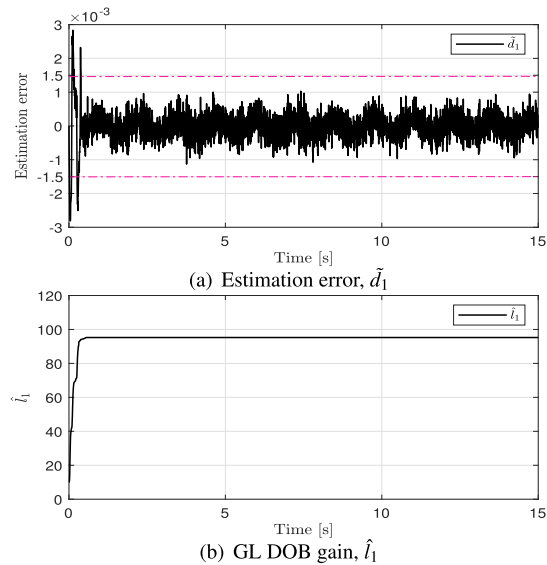


FIGURE 11. Experimental results: Estimation error and GL DOB gain.

The position tracking control performance is presented in Fig. 8. In all cases, the position tracked the desired position trajectory well. The tracking errors and GL control gains are displayed in Fig. 9. The dash-dotted line represents the desired upper bound of the error. The tracking errors in Cases 2 and 3 were lower than in Case 1. In Case 2, although the disturbances were not compensated for, the tracking errors were suppressed in the desired bound by the GL control gains. In Case 3, as the disturbance was considered in the control input (49), the GL control gains were updated to a smaller value than in Case 2. The proposed method (Case 3) improved control performance compared to Case 2. The control inputs of Cases 1 to 3 are presented in Fig. 10. In common with simulation results, the higher peaking of the input in Case 1 can be observed than Cases 2 and 3 at $t=0$ s. Although the

GL control gains become larger than the constant gain in a steady-state, the same effort of control input can be observed in all cases in Fig. 10. The control input comprised the multiplication between the tracking error and GL gain. Therefore, an increased GL gain does not affect the control input because the tracking error simultaneously decreases. The disturbance estimation error and GL DOB gains are presented in Fig. 11. We can observe that the GL DOB gains were updated to suppress the estimation error in the desired bound. From experimental results, the desired control and disturbance estimation performance were successfully obtained using the GL gains, which are automatically tuned to achieve the desired performance.

VI. CONCLUSION

This paper proposed the GL gain for a backstepping controller and a DOB for nonlinear systems. The GL gain update law was proposed to adapt the control and observer gain according to the direction that minimizes the cost function. The theoretical analysis were demonstrate from simulation and experiment results. The control and DOB gains were simultaneously tuned to achieve improved performance; thus, the time consumption for tuning was reduced in the experiment. The proposed method can avoid the peaking phenomenon in the control input through the GL gain. In addition, the tracking error of the proposed method was reduced compared with the conventional method. In a future study, the reinforcement-learning-based varying control gain for achieving the desired performance with a stability guarantee will be investigated for various applications in real-time industrial practice.

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