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Observer Based Control for a Class of Systems with Output Deadzone Nonlinearity

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Abstract

In this paper, a combination of model based adaptive design along with adaptive linear output feedback controller is used to compensate for robotic manipulator with output deadzone nonlinearity. The deadzone dynamics are utilized to adaptively estimate the deadzone parameter and a switching function is designed to eliminate the error produced in the adaptive observer dynamics. The overall design of the closed loop system ensures stability in the BIBO criterion.

Keywords

Adaptive Output Observer, Deadzone Compensation, Robot Manipulator, Sliding Mode Control

1. Introduction

Deadzone nonlinearity is a common problem that arises in many dynamic systems. It may be affecting the input as an actuator problem or the output of the system as a physical sensor measurement problem. Most papers address the problem of deadzone as an actuator thereby affecting the input side [1]-[3]. The output deadzone problem was also investigated for example by [4] utilizing adaptive inverse control scheme which ensured reduction in tracking errors for a class of systems with strict feedback topology. Adaptive fuzzy output feedback control of nonlinear systems with input deadzone presented in [5] ensuring BIBO of all closed loop signals. An abundant number of papers employed fuzzy logic (FLS), neural networks (NN), and sliding mode control(SMC) schemes because of the discontinuous nonlinear nature of the deadzone nonlinearity [6]-[8]. The complexities of NN, FLSs, and SMC control methods make it difficult to implement for practical applications such as robotics manipulator. They are too complex to be feasible for real application.

Robotic manipulators driven by motors with a deadzone nonlinearity in the driving gears produce imprecisions which are amplified by the robotic arm gains [7]. Sliding mode methods have been used by several researchers to alleviate the deleterious effects of the deadzone nonlinearity with several of them reporting large improvement in the error reduction and a bounded input bounded output stability condition is achieved [9] [10]. That type of design although shows great improvements in the set out objectives, suffers from an inherent problem known as chattering caused by the sign function used in the control law. In addition, the sliding mode control method deals with actuator deadzone where the deadzone function affects the input of the system. Input deadzone problem is easier to tackle since all states of the system are available to be used directly in the sliding mode controller [11]. In reality, numerous non-smooth nonlinearities, including deadzone and saturation, appear in the output of a dynamic system. These non-smooth nonlinearities' characteristics have a significant negative impact on the performance of the nonlinear systems and can potentially eliminate their stability. The controller design and stability analysis for nonlinear systems with output restrictions are more challenging and sophisticated when compared to nonlinear systems with input constraints [7] [12] [13]. One example was presented in [14] where they applied a novel method based on the Multidimensional Taylor Network (MTN) to an output deadzone problem. However, the authors assumed that all state signals were accessible for measurement and could be used to track the desired reference trajectory.

In this paper, the output deadzone problem is addressed under the assumption that the systems' states are not measurable. Nevertheless, it is assumed that the system's model is known and only the deadzone spacing parameter is assumed to be unknown, to which an adaptive update law is designed to estimate it. Once the system dynamics are identified an observer dynamics are developed and used in a classical way to estimate the system states. Consequently, the estimates are combined with adaptive nonlinear controller designed through the Lyapunov method guaranteeing BIBO stability of the overall closed loop system dynamics. The utilization of a combination of model-based adaptive design and adaptive linear output feedback controller to compensate for a robot manipulator with output dead zone nonlinearity. While the specific method used in the paper may not have been directly verified in similar robot control problems, the underlying principles of model-based adaptive design and adaptive control have been extensively studied and applied in various control systems.

The framework for the control design presented in this paper is laid forth as follows: Section III describes the deadzone function's mathematical representation, parameters, and underlying assumptions. The creation of an adaptive observer that estimates the deadzone parameters and system states and uses these estimations to accomplish desired control objectives is covered in section IV. The effectiveness and practical use of the suggested architecture are illustrated in section V with a second-order system example that shows the observer's performance in following a reference trajectory. Meanwhile, In the last section, simulations are presented to show the efficacy of the proposed design and stability of the overall system.

2. Modelling the Dynamics of Output Deadzone Nonlinearity

As seen in **Figure 1**, a typical illustration of a non-symmetrical deadzone nonlinearity is as in [4] follows.

$$Dz(x) = \begin{cases} m(x - d_r), & \text{if } x > d_r \\ 0, & \text{if } -d_l < x < d_r \\ m(x + d_l), & \text{if } x < -d_l \end{cases} \tag{1}$$

where $Dz(x)$ denotes the output of deadzone function, $x(t)$ the output of a plant, m is the slope of the lines, $|d_r - d_l|$ is the width of the deadzone distance, and x is the input of the plant block as shown in **Figure 1**. Although the width of the deadzone spacing is assumed not to be exactly known, an upper bounds on it is given by

$$|d_r - d_l| \le d_M \tag{2}$$

where d_M is a positive scalar. Output deadzone may also be written as

$$Dz(x) = x - \text{Sat}(x) \tag{3}$$

where Sat(x) represents a non-symmetrical saturation function given by

$$\text{Sat}(x) = \begin{cases} d_r, & \text{if } x > d_r \\ x, & \text{if } -d_l < x < d_r \\ -d_l, & \text{if } x < -d_l \end{cases} \tag{4}$$

By defining a logical switching operators

$$\chi_r = \begin{cases} 1, & \text{if } x > 0 \\ 0, & \text{otherwise} \end{cases} \tag{5}$$

$$\chi_l = \begin{cases} 1, & \text{if } x < 0 \\ 0, & \text{otherwise} \end{cases} \tag{6}$$

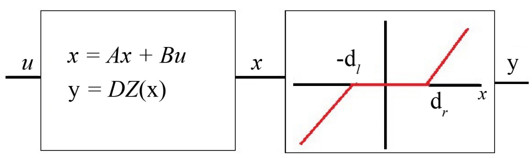

Figure 1. Overall system block diagram with output deadzone.

The goal is to modify the output $y(t)$ by adding an adaptive saturation function to negate the effect of the subtractive saturation effect caused by the output deadzone nonlinearity. Meanwhile, the logical indicators, $\bar{\chi} = [\chi_r \quad \chi_l]$ can be implemented by utilizing the definition of a sign function given as

$$\operatorname{sgn}(y)=\begin{cases}1, & \text{if } y>0\\ -1, & \text{if } y<0\end{cases} \tag{7}$$

To obtain a smoothly differentiable implementation of (11), the $\operatorname{sgn}(x)$ function is replaced with

$$\operatorname{sgn}(x_d)=\operatorname{Tanh}(k_s y), \tag{8}$$

with $k_s>0$ appropriately selected with high value to force fast switching of the hyperbolic tangent fucntion. Hence, rewriting Equations (5) and (6) as

$$\chi_r=\frac{1+\operatorname{sgn}(y)}{2} \tag{9}$$

$$\chi_l=\frac{1-\operatorname{sgn}(y)}{2} \tag{10}$$

Then, the dynamics of the non-symmetrical deadzone presented in (3) can be rewritten as follows

$$y=Dz(x)=x(t)-\chi_l d_l-\chi_r d_r, \tag{11}$$

or more compactly written by using vector notation as

$$y=Dz(x)=x(t)-\bar{\chi}d, \tag{12}$$

where $\bar{\chi}\in R^{1\times 2}$ are logical indicators $[\chi_r \quad \chi_l]$, and d is the vector of asymmetrical deadzone parameters $[d_r \quad d_l]^{\mathrm{T}}$.

To proceed with the design of the compensator the following assumptions are required:

* (A1) The deadzone parameters $d_r>0$ and $-d_l<0$.
* (A2) The initial measurement of the deadzone is known and equal to *d*.
* (A3) Without any loss of generality slope *m* is positive and is set to 1.
* (A4) The output of the deadzone block $y=Dz(x)$ is available for measurement while the system's dynamic states *x* are not.

Assumptions (A1) and (A2) are the actual physical attributes of a real industrial deadzone and are adopted in [15]. Therefore, the saturation function given by (4) is physically bounded by

$$\|\operatorname{Sat}(y)\|=\|\bar{\chi}d\|\le d_M. \tag{13}$$

3. Adaptive Observer Design

The decomposition of the deadzone nolinearity into a linear term combined with a saturation term as in Equation (3) motivated the suggested solution of this paper. The strategy involves designing a modified Luenberger dynmaic observer [15] of the system by including an output deadzone function. Subsequently, utilize the the states of obtain observer to achieve the desired objective of tracking a reference trajectory as well as adaptively obtaining an accurate estimate the saturation spacing of the deadzone function. Consequently, the estimated saturation function is added to the output of the original system to cancel the saturation effect from the actual deadzone as shown in the block diagram of Figure 2.

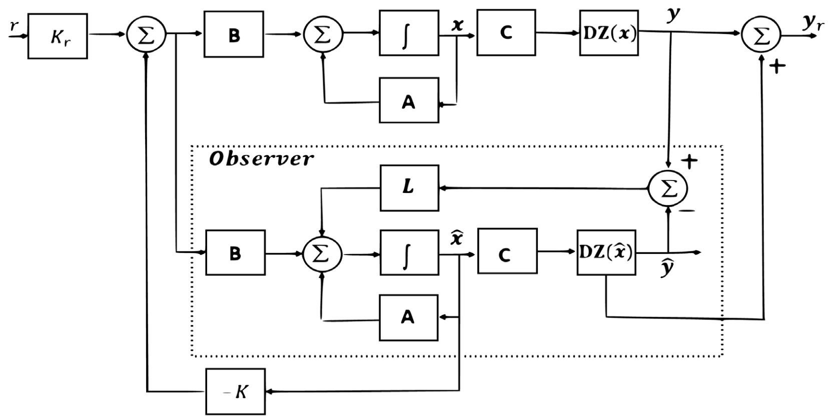

Figure 2. Overall system block diagram of the adaptive observer with the deadzone estimation function.

Considering the following nonlinear systems with output deadzone nonlinearity described as

$$\begin{aligned} \dot{x} &= Ax + Bu \\ y &= Dz(x) = Cx - \mathrm{Sat}(Cx) \end{aligned} \tag{14}$$

where the matrices $A \in R^{n\times m}$, $B \in R^{n\times 1}$ and $C \in R^{n\times 1}$ are given by

$$A = \begin{bmatrix} 0 & 1 & \cdots & 0 \\ & & \ddots & \\ 0 & 0 & & 1 \\ 0 & 0 & \cdots & 0 \end{bmatrix}; B = \begin{bmatrix} 0 \\ \vdots \\ 0 \\ 1 \end{bmatrix}; C^{\mathrm{T}} = \begin{bmatrix} 1 \\ \vdots \\ 0 \\ 0 \end{bmatrix}. \tag{15}$$

The desired observer dynamics are given by

$$\dot{\hat{x}} = A\hat{x} + L(y - \hat{y}) \tag{16}$$

$$\hat{y} = C\hat{x} - \mathrm{Sat}(C\hat{x}) \tag{17}$$

where $L \in R^{1\times n}$. Utilizing equation (14) and (17) to replace $y - \hat{y}$ in (16) as

$$\dot{\hat{x}} = A\hat{x} + L\left[Cx - \mathrm{Sat}(Cx) - C\hat{x} + \mathrm{Sat}(C\hat{x})\right]. \tag{18}$$

Consequently, empolying the dynamics of deadzone given in (11) to express (18) as

$$\dot{\hat{x}} = A\hat{x} + L\left(Cx - C\hat{x} - \overline{\chi}d + \overline{\chi}\hat{d}\right) \tag{19}$$

$$\dot{\hat{x}} = A\hat{x} + L\left(C\tilde{x} - \overline{\chi}\tilde{d}\right), \tag{20}$$

where $\tilde{x} = x - \hat{x}$ represents the observer state error, and

$$\tilde{d} = \begin{bmatrix} d_r - \hat{d}_r \\ d_l - \hat{d}_l \end{bmatrix}; \ \overline{\chi} = [\chi_r \quad \chi_l]. \tag{21}$$

Defining the output observer error dynamics as $\tilde{y} = y - \hat{y} = C\tilde{x}$ results in the following

$$\dot{\tilde{x}} = Ax + Bu - A\hat{x} - LC\left(\tilde{x} - \overline{\chi}\tilde{d}\right) \quad (22)$$

$$= A\tilde{x} + Bu - LC\left(\tilde{x} - \overline{\chi}\tilde{d}\right) \quad (23)$$

$$= \left(A - LC\right)\tilde{x} + Bu - LC\overline{\chi}\tilde{d}. \quad (24)$$

A suggested adaptation update law for $\hat{d}$ is given by

$$\dot{\hat{d}} = -\sigma\tilde{y}PLC\overline{\chi} \quad (25)$$

where $\tilde{y} = y - \hat{y}$ is the output observer error. Once again, by ensuring that the observer output $\hat{y}(t)$ is asymptotically tracking the actual plant output $y(t)$, an exact estimate of the saturation parameter will be determined and simply added to the output as inverse saturation function

$$y(t) = C\left\{x(t) - \left(d - \hat{d}\right)\overline{\chi}\right\} \quad (26)$$

Since $d - \hat{d} \to 0$ asymptotically, the effect of saturation part of the deadzone function will be eliminated thereby eliminating the deadzone effect in total.

Meanwhile, output mismatch error, expressed as $\tilde{d} = d - \hat{d}$, caused by the inexact cancellation of the saturation inverse block estimated parameters can be treated as a disturbance and a robust term consisting of a hyperbolic tangent function as was shown in [16] [17]. To parameterize $\tilde{y}(t)$ Equation (11) is used in the following manner

$$\tilde{y}(t) = y - \hat{y} = C\left(x - \hat{x}\right) - \overline{\chi}\left(d - \hat{d}\right), \quad (27)$$

or may simply written as

$$\tilde{y}(t) = C\tilde{x} - \overline{\chi}\tilde{d}, \quad (28)$$

where $\tilde{d}$ is the deadzone parameters estimation error whose dynamics were given earlier in (25). Therefore, the deadzone effect noted by the term $d^{\mathrm{T}}\overline{\chi}$ in (12) can be cancelled by simply adding $\overline{\chi}\hat{d}$ to the output of the system $y(t)$. To achieve proper tracking and global bounded stability of the overall system, the following adaptive controller is proposed

$$u_d(t) = -\alpha B^{\mathrm{T}}P\tilde{y} - \alpha B^{\mathrm{T}}PLC\chi\tilde{d} \quad (29)$$

where $\alpha > 0$, and P is the positive definite symmetric solution of the Algebraic Riccati equation (ARE). The properties of the controller (29) is stated in the following Theorem:

Theorem 4.1 *The adaptive control law specified in (29) and the adaptation update law (25) are devised to guarantee asymptotic tracking of the plant by the modified observer system, as defined in (17), for the output deadzone system outlined in (14). Consequently, this approach ensures overall closed-loop stability and boundedness of the tracking error, thereby effectively mitigating the impact of the deadzone on the output.*

To prove Theorem 4.1, the following positive definite control Lyapunov function is proposed:

$$V = \tilde{y}P\tilde{y}^{\mathrm{T}} + \frac{\tilde{d}^2}{2\sigma}. \tag{30}$$

Differentiating along the trajectories of the system and substituting for the closed loop dynamics yields

$$\begin{aligned} \dot{V} &= \dot{\tilde{y}}P\tilde{y}^{\mathrm{T}} + \tilde{y}P\dot{\tilde{y}}^{\mathrm{T}} + \frac{\tilde{d}\dot{\hat{d}}}{\sigma} \\ &= C\left[(A-LC)e_x + Bu - LC\overline{\chi}\tilde{d}\right]Pe_x^{\mathrm{T}}C^{\mathrm{T}} \\ &\quad + Ce_xP\left[(A-LC)e_x + Bu - LC\overline{\chi}\tilde{d}\right]^{\mathrm{T}}C^{\mathrm{T}} + \sigma^{-1}\tilde{d}\dot{\hat{d}} \end{aligned} \tag{31}$$

Regrouping terms while noting again that $Ce_x = \tilde{y}$ leads to

$$\dot{V} = \tilde{y}\left[(A-LC)^{\mathrm{T}}P + (A-LC)P\right]\tilde{y}^{\mathrm{T}} + 2\tilde{y}P\left(Bu - LC\overline{\chi}\tilde{d}\right) - \sigma^{-1}\tilde{d}\dot{\hat{d}}. \tag{32}$$

inserting the suggested control law (29) into (32) yeilds

$$= \tilde{y}\left[(A-LC)^{\mathrm{T}}P + (A-LC)P - 2\alpha PBB^{\mathrm{T}}P\right]\tilde{y}^{\mathrm{T}} - 2\tilde{y}PLC\overline{\chi}\tilde{d} + \sigma^{-1}\tilde{d}\dot{\hat{d}}. \tag{33}$$

The first term can be simplified by solving the Algebraic Reccati Equation given by

$$(A-LC)^{\mathrm{T}}P + P(A-LC) - 2\alpha PBB^{\mathrm{T}}P = -Q \tag{34}$$

where P and Q are positive definite matrices, which simplifies (33) to

$$\dot{V} = -\tilde{y}^{\mathrm{T}}Q\tilde{y} - 2\tilde{d}\left(\tilde{y}PLC\overline{\chi} - \sigma^{-1}\dot{\hat{d}}\right). \tag{35}$$

The second term is eliminated by the adaptive update law for $\hat{d}$ given in Equation (25) which renders (35) negative as follows

$$\dot{V} = -\tilde{y}^{\mathrm{T}}Q\tilde{y}. \tag{36}$$

Therefore the output observer error dynamics $\tilde{y}(t) \to 0$ as $t \to \infty$ leading to $\hat{y} \to y(t)$ asymptotically. The dynamics of the observer $\hat{y} = C\hat{x} - \overline{\chi}\hat{d}$ can be used in in two ways. The first part $C\hat{x}$ to satisfy any system dynamics control objectives such as tracking or regulation; while the second part $\overline{\chi}\hat{d}$ is used to negate the deadzone effect on the output of the overall closed loop system output y as will be demonstrated in the following section.

4. Illustrative Example and Simulations

To illustrate the efficacy of the proposed adaptive observer of system with output deadzone nonlinearity a second order desired reference model is selected for tracking. Initially, the classical Luenberber Observer design methodology will be applied to the system under the assumption that the output is not suffering from an output deadzone function. Instead, the deadzone function will be incorporated at a later stage in both the system as well as the observer dynamics. Consider a second order system defined as

$$\ddot{x} + 2\zeta\omega_n\dot{x} + \omega_n x = u, \tag{37}$$

and, without any loss of generality, the reference signal is $r(t) = 5\sin(2\pi t)$, $\zeta = 1$, and $\omega_n = 2\pi$ rad/s. Then the state space representation of the system is given by

$$\begin{aligned} \dot{x}_1 &= x_2 \\ \dot{x}_2 &= -x_1 - 2x_2 + u \\ y &= Dz\left(\begin{bmatrix}1 & 0\end{bmatrix}x\right) = x_1 - \mathrm{Sat}(x_1). \end{aligned} \tag{38}$$

Therefore, the state space matrices of the system can be written as

$$A = \begin{bmatrix} 0 & 1 \\ -1 & -2 \end{bmatrix};\ B = \begin{bmatrix} 0 \\ 1 \end{bmatrix};\ C^{\mathrm{T}} = \begin{bmatrix} 1 \\ 0 \end{bmatrix}. \tag{39}$$

Meanwhile, the L-matrix of the observer gains are chosen as to place the poles at (−4.0 −10.0) to insure the stability of the desired tracked model yielding the following

$$L = \begin{bmatrix} -1.25 \\ -1.62 \end{bmatrix}. \tag{40}$$

Hence, the observer dynamics may be written as

$$\begin{aligned} \dot{\hat{x}}_1 &= \hat{x}_2 \\ \dot{\hat{x}}_2 &= -\hat{x}_2 - 2\hat{x}_2 \\ \hat{y} &= \hat{x}_1 - \mathrm{Sat}(\hat{x}_1), \end{aligned} \tag{41}$$

For the control law, a simple PD controller is designed as

$$u = \alpha B^{\mathrm{T}} P\tilde{y} = -k_p(y - \hat{y}) - k_d(y - \hat{y}) + r(t) \tag{42}$$

where k_p and k_d are the obtained by solving the Algebraic Riccati Equation given in 30 and equating each term appropriately. The output of the system will be added to the observed saturation estimates $\mathrm{sat}(c\hat{x}_1)$ to negate the effect of the actual saturation component of the output deadzone nonlinearity. The deadzone spacing parameter can be easily predetermined and measured. The reference point is chosen to be at the center of the deadzone spacing. Without any loss of generality, deadzone parameters are set to $d_r = -d_l = 1$ with d^* being the adaptation that estimates its value as given by Equation (25).

In **Figure 3** and **Figure 4**, the visual representations offer insights into the system's behavior concerning the desired trajectory $\theta_d = 2\sin(2\pi t)$. The figures provide a detailed view of the output tracking performance and output tracking error over time respectively. Moving on to **Figure 5** and **Figure 6**, the focus shifts to the observer state $\hat{x}_1$ tracking of the state x_1 performances and the tracking error, respectively. These illustrations capture noteworthy events, such as sudden vertical displacements are gradually decreasing in occurrences which clearly demonstrate the role of $\mathrm{Sat}(C\hat{x})$ in mitigating the impact of the dead-zone spacing on the system's output $y(t)$. Similarly, **Figure 7** confirms the asymptotic tracking of $x_2(t)$ state by the observer state $\hat{x}_2$. Lastly, **Figure 8** provides a visual representation of the dynamic upper bounding adaptation $\hat{\beta}$. The figure serves as evidence of the bounded nature of this adaptation, showcasing how it evolves over the course of the system's operation. This insight contributes to a comprehensive understanding of the adaptive mechanisms at play in the control system.

Figure 8 demonstrates the evolution of the dynamic upper bounding adaptation $\hat{\beta}$ which proofs its boundedness.

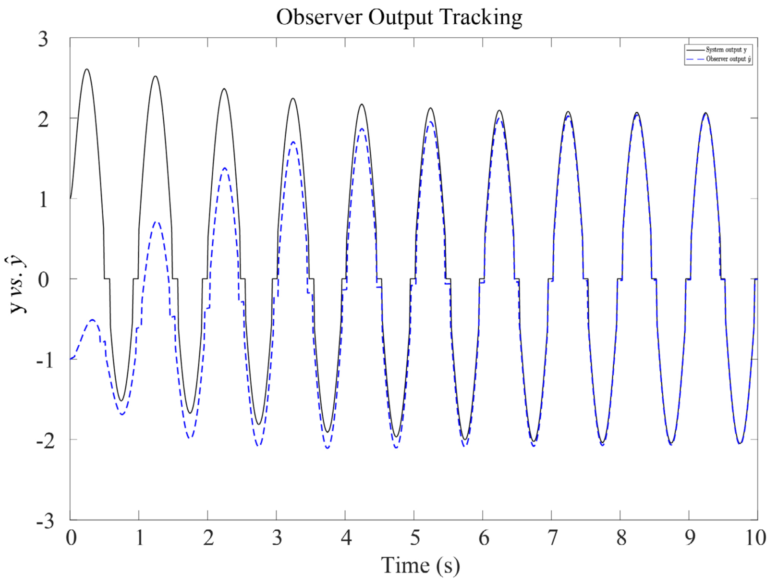

Figure 3. Observer output $\hat{y}(t)$ tracking of system's output $y(t)$ affected by deadzone.

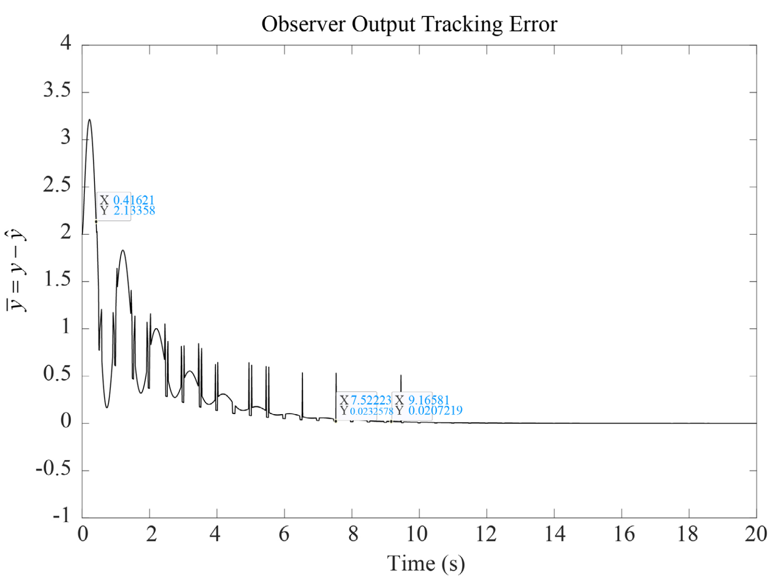

Figure 4. Observer output tracking error $\hat{y}(t)-y(t)$ approaching zero asymptotically.

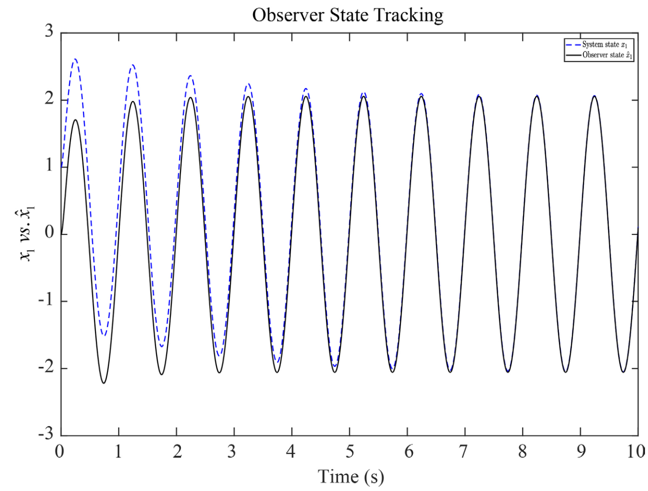

Figure 5. Observer state $\hat{x}_1(t)$ tracking system's state $x_1(t)$.

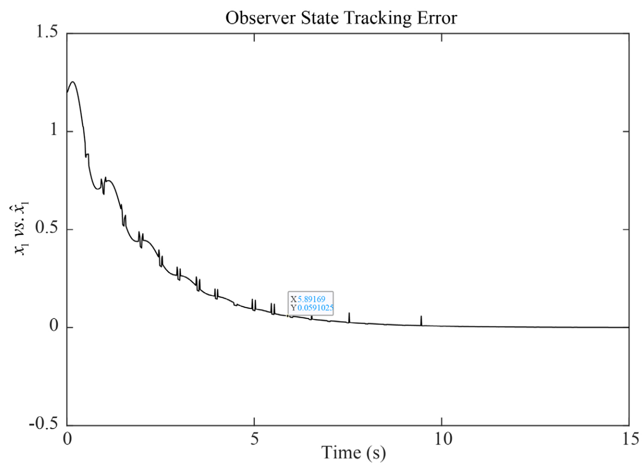

Figure 6. State tracking error $\hat{x}_1(t) - x_1(t)$ approaching zero asymptotically.

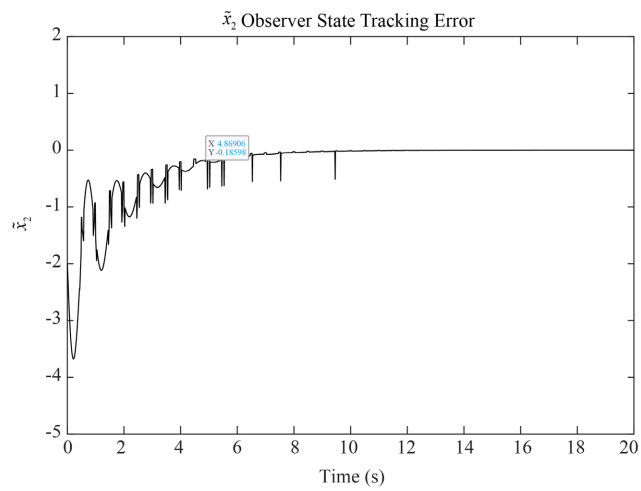

Figure 7. State tracking error $\hat{x}_2(t) - x_2(t)$ approaching zero asymptotically.

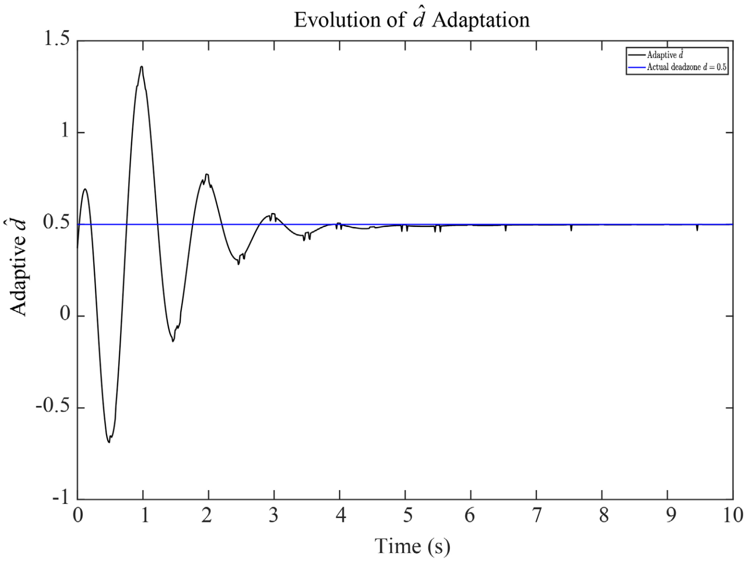

Figure 8. The adaptation $\hat{d}$ progression.

5. Conclusions

In conclusion, this paper proposed an observer-based control approach for systems with output deadzone nonlinearity, focusing on the compensation of robotic manipulators affected by deadzone in the output. The key contributions include the utilization of a combination of model-based adaptive design and an adaptive linear output feedback controller. An adaptive output observer was developed to estimate the deadzone parameter, and a switching function was designed to eliminate the error produced in the adaptive observer dynamics. The overall closed-loop system design ensures stability in the BIBO criterion. When using adaptive methods to estimate dead zone parameters, mitigating the impact of noise and uncertainty on parameter estimation is crucial. Techniques such as filtering, regularization, and adaptive algorithms with robustness features can help reduce the effects of noise and uncertainty in parameter estimation. Additionally, incorporating system identification methods and experimental validation can improve the accuracy and reliability of parameter estimates in practical applications. Theoretical formulations, including the modeling of deadzone dynamics, adaptive observer design, and stability analysis, were presented. The proposed approach was compared to existing methods, such as fuzzy logic, neural networks, and sliding mode control, which are often too complex for practical applications like robotic manipulators. The focus on output deadzone, where the deadzone function affects the system's output, presented additional challenges compared to input deadzone problems. While the specific method used in the paper may not have been directly verified in similar robot control problems, the underlying principles of model-based adaptive design and adaptive control have been extensively studied and applied in various control systems.

Simulation results were provided to demonstrate the effectiveness of the proposed design. A second-order system with a desired reference trajectory was used for illustration. The adaptive observer, combined with a control law, successfully tracked the reference trajectory and reduced the effects of deadzone on the system's output. The control effort and adaptation evolution were also analyzed, showcasing the robustness of the proposed approach.

In summary, the developed observer-based control strategy offers a practical solution for systems affected by output deadzone nonlinearity, especially in the context of robotic manipulators. The proposed methodology provides a foundation for further research and applications in real-world scenarios where deadzone compensation is crucial for system performance and stability. However, there may be challenges such as the convergence rate of the error, which could be too slow or potentially unstable depending on the specific implementation and tuning parameters. Further theoretical analysis and experimental validation may be needed to assess the performance of the observer in different scenarios.

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Conflicts of Interest

The authors declare no conflicts of interest regarding the publication of this paper.

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