Volume 8, Issue 7, pp. 114-118, 2024.
International Journal of Scientific Engineering and Science
ISSN (Online): 2456-7361

Finite Time Control of Parameterized Systems with Dead Zone and State Constraints

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Abstract**—***This paper investigates the problem of adaptive finite-time tracking control for nonlinear parameterized systems subject to full state constraints and dead-zone. By utilizing the finite-time stability theory, one to one nonlinear mapping and dynamic surface control (DSC), a novel adaptive tracking control is proposed. By using the defined compact set in stability analysis, all the signals in the close-loop system are proved to be semi-globally practical finite-time bounded (SGPFB), and state constraint is not violated. Numerical simulation has verified the effectiveness of the control strategy.*

Keywords**—** *Adaptive finite-time control, Dead-zone, Full state constraints.*

I. INTRODUCTION

In recent years, dynamic surface control technology has been widely applied in nonlinear system control and has achieved good results in [1-4]. Based on the DSC method, reference [3] solved the controller design problem of a class of strict feedback systems and provides Lyapunov stability analysis. With the help of the implicit function theorem, an adaptive control strategy is proposed for a class of pure feedback nonlinear systems via DSC in [4].

In addition, in real-world systems, due to factors such as safety and location, the system's state must be limited within a certain range. For example, the literature [5] defined a set of Barrier Lyapunov functions that constrain the state at each step of the design process. However, in practical applications, this method cannot accurately constrain the state. On this basis, people have proposed the method of introducing nonlinear mapping to transform constrained problems into constrained problems, thereby enabling controller design in [6-8]. The nonlinear mappings in references [6] and [7] are based on logarithmic functions, while reference [8] adopts a new fractional form.

Specifically, control systems in reality often exhibit nonlinear phenomena in the controller, with the most common form being dead zones. Reference [9] linearized the dead zone and successfully separated the control law u for controller design. At the same time, specific systems also have time requirements, leading to the emergence of finite time control in [10-12]. Inspired by the above achievements, this paper studies the finite time control problem of a class of constrained parameterized systems with dead zones. The main work is as follows: (1) Introducing non logarithmic mapping to transform the constrained system into an unconstrained system, and using dynamic surface control method for controller design to avoid the problem of parameter explosion. (2) After transformation, the parameterized system becomes a strict feedback system, and neural networks are used to approximate unknown functions to handle the unknown nonlinear terms of the system.

II. SYSTEM DESCRPTION AND PROBLEM STATEMENT

Consider the following nonlinear systems:

$$\begin{cases} \dot{x}_i = v_i^T f_i(\bar{x}_i) + \varphi_i x_{i+1}, i = 1, L, n\text{-}1 \\ \dot{x}_n = v_n^T f_n(\bar{x}_n) + \varphi_n Q(u(t)) \\ y = x_1 \end{cases} \tag{1}$$

where $\bar{x}_i = [x_1 \cdots x_i]^T \in R^i$, y denote the system states and output. $v_i \in R^m$ is the unknown constant vector , $\phi_i(\bar{x}_i)$ is known nonlinear function vector. All the states are constrained in predefined compact set, i.e., $|x_i| < k_{ci} (i = 1, \cdots, n)$ are predefined positive constants. The dead-zone input $u(t)$ can be described as

$$Q(u(t)) = \begin{cases} m_r(u(t) - b_r), & u(t) \ge b_r \\ 0, & \text{-b}_l < u(t) < b_r \\ m_l(u(t) + b_l), & \text{u(t)} \le \text{-b}_l \end{cases} \tag{2}$$

Control objective: Design a controller u that enables the output of system (1) to track the desired trajectory and satisfy the constraint conditions.

Assumption 1 [5] The desired trajectory vector $x_d = [y_d, \dot{y}_d, \ddot{y}_d]^T \in \Omega_d$ is constants and available with known compact set $\Omega_d = \left\{ x_d : y_d^2 + \dot{y}_d^2 + \ddot{y}_d^2 \le B_0 \right\} \in R^3$, and $|y_d| < B_1 \le \min\left\{ k_{b_1}, k_{b_2} \right\}$, where B_0 , B_1 are two known positive constants.

Lemma 1 [110] considering the system $\dot{x} = f(x,u)$, for positive function $V(x)$, if there exist scalars $\alpha > 0$, $\frac{1}{2} < \beta < 1$ and $\mu > 0$, such that $\dot{V}(x) \le \text{-}\alpha V^{\beta}(x) + \mu$ then the nonlinear system $\dot{x} = f(x,u)$ is SGPFS.

Lemma 2 [10] For any real variables x , y , there any given positive constants a , b and c , it holds the inequality such that

International Journal of Scientific Engineering and Science
Volume 8, Issue 7, pp. 114-118, 2024. ISSN (Online): 2456-7361

$$|x|^a |y|^b \le \frac{a}{a+b} c |x|^{a+b} + \frac{b}{a+b} c^{-\frac{a}{b}} |y|^{a+b} \quad (3)$$

Lemma 3 [10] For $x_j \in R, j = 1 \cdots n, 0 < p \le 1$, it holds the inequality such that

$$\left(\sum_{j=1}^{n} |x_j| \right)^p \le \sum_{j=1}^{n} |x_j|^p \le n^{1-p} \left(\sum_{j=1}^{n} |x_j| \right)^p \quad (4)$$

III. Controller Design and Stability Analysis

In order to carry out full state constraints, we introduce the following one to one mapping:

$$s_i = \ln \frac{k_{ci} + x_i}{k_{ci} - x_i}, i = 1, \cdots, n \quad (5)$$

Then we get

$$\dot{s}_i = \frac{e^{s_i} + e^{-s_i} + 2}{2k_{ci}} \dot{x}_i, i = 1, \cdots, n \quad (6)$$

The system（1）can be rewritten as follows：

$$\begin{cases} \dot{s}_i = f_i(\bar{s}_{i+1}) + s_{i+1}, i = 1, \cdots, n-1 \\ \dot{s}_n = f_n(\bar{s}_n) + k_n(s_n)\varphi_n Q(u(t)) \end{cases} \quad (7)$$

where $\bar{s}_i = [s_1, \cdots, s_i]^T$, $k_i(s_i) = \left(e^{s_i} + e^{-s_i} + 2\right) / 2k_{ci}$, $f_i(s_{i+1}) = k_i(s_i)[v_i^T \phi_i(\bar{x}_i) + \varphi_i x_{i+1}] - s_{i+1}, i = 1, \cdots, n-1$, $f_n(\bar{s}_n) = k_n(s_n) v_n^T \phi_n(\bar{x}_n)$.

Let $\hat{y}_d = \ln \dfrac{k_{c1} + y_d}{k_{c1} - y_d}$. Suppose $\Omega_{z_i} = R^{i+3}$ be a given compact set, and $W_{hi}^{*T} S_i(Z_i)$ be the approximation of BRF NNs over the compact set Ω_{z_i} to $h_i(Z_i)$, where $h_i(Z_i)$ will be given later. Then, $h_i(Z_i) = W_{hi}^{*T} S_i(Z_i) + \varepsilon_{hi}(Z_i)$, where $Z_i = [Z_{i1}, \cdots, Z_{iq}]^T \in R^{iq}$, and the basis function vector $S_i(Z_i) = [s_{i1}(Z_1), \cdots, s_{il_j}(Z_i)]^T \in R^{l_i}$ with $s_{ij}(Z_i)$ being choose as follows:

$$s_{ij}(Z_i) = \exp\left[-\frac{(Z_i - \mu_{ij})^T (Z_i - \mu_{ij})}{\phi_{ij}^2} \right], j = 1, \cdots, l_i, i = 1, \cdots, n,$$

$\mu_{ij} = [\mu_{ij1}, \mu_{ij2}, \cdots, \mu_{ijq_{ij}}]^T$ is the center of the receptive field with $q_{ij} = n + 3$, and ϕ_{ij} is width of the Gaussian function.

For clarity, some notations are defined as follows:

$\bar{z}_i = [z_1, \cdots, z_i]^T$, $\bar{y}_j = [y_1, \cdots, y_j]^T$, $y_j = \omega_j - \alpha_{j-1}$, $j = 2, \cdots, n$.

$\theta_i = \|W_{hi}^*\|^2$, $\bar{\hat{\theta}}_i = [\hat{\theta}_1, \cdots, \hat{\theta}_i]^T$, $V_{z_i} = \frac{1}{2} z_i^2$, $z_i = s_i - \omega_i$ $i = 1, \cdots, n$.

Step 1: Let $\omega_1 = \hat{y}_d$, we obtain the time derivative of z_1

$$\dot{z}_1 = s_2 + f_1(\bar{s}_2) - \dot{\omega}_1$$

Then the derivative of V_{z_1} with respect to t is

$$\begin{aligned} \dot{V}_{z_1} &= z_1[z_2 + y_2 + \alpha_1 + h_1(Z_1)] - 3z_1^2 \\ &= z_1[z_2 + y_2 + \alpha_1 + W_{h1}^{*T} S_1(Z_1) + \varepsilon_{h1}(Z_1)] - 3z_1^2 \\ &\le z_1[z_2 + y_2 + \alpha_1] + \frac{1}{2a_1^2} z_1^2 \theta_1 \|S_1(Z_1)\|^2 \\ &\quad + \frac{a_1^2}{2} + z_1 \varepsilon_{h1}(Z_1) - 3z_1^2 \end{aligned} \quad (8)$$

where $h_1(Z_1) = f_1(\bar{s}_2) - \dot{\omega}_1 + 3z_1$ **(1)** and $a_1 > 0$ is a design constant.

Design the virtual control α_1 as follows:

$$\alpha_1 = -k_1 z_1^{2\beta-1} - \frac{z_1}{2a_1^2} \hat{\theta}_1 \|S_1(Z_1)\|^2 \quad (9)$$

where k_1 is a design constant that we will choose later, $\hat{\theta}_1$ is the estimate of θ_1 at time t.

The following adaptive law is used to update the unknown parameter θ_1 for $i = 1$. **(2)**

$$\dot{\hat{\theta}}_i = \gamma_i [\frac{1}{2a_i^2} z_i^2 \|S_1(Z_1)\|^2 - \sigma_i \hat{\theta}_i] \quad (10)$$

where γ_i, a_i and σ_i are strictly positive constants and $\hat{\theta}_i$ is the estimate of θ_i at time t.

Define ω_2 in such a way that

$$\tau_2 \dot{\omega}_2 + \omega_2 = \alpha_1, \omega_2(0) = \alpha_1(0) \quad (11)$$

where τ_2 is a design constant that we will choose later.

Since $s_2 = z_2 + y_2 - k_1 z_1^{2\beta-1} - z_1 \hat{\theta}_1 \|S_1(Z_1)\|^2 / 2a_1^2$, using young's inequality, we obtain

$$\begin{aligned} \dot{V}_{z_1} &\le -k_1 z_1^{2\beta} - \frac{z_1^2 \tilde{\theta}_1 \|S_1(Z_1)\|^2}{2a_1^2} \\ &\quad + \frac{z_2^2}{4} + \frac{y_2^2}{4} + \frac{a_1^2}{2} + z_1 \eta_1 - z_1^2 \end{aligned} \quad (12)$$

where continuous function η_1 satisfies $|\varepsilon_{h1}(Z_1)| \le \eta_1$. **(3)**

From young's inequality, we have $|z_1| \eta_1 \le z_1^2 + \frac{1}{4} \eta_1^2$, **(4)** then we get

$$\dot{V}_{z_1} \le -k_1 z_1^{2\beta} - \frac{z_1^2 \tilde{\theta}_1 \|S_1(Z_1)\|^2}{2a_1^2} + \frac{z_2^2}{4} + \frac{y_2^2}{4} + \frac{a_1^2}{2} + \frac{1}{4}\eta_1^2 \quad (13)$$

Noting Assumption 1, we have $\left|\dot{y}_2 + \frac{y_2}{\tau_2}\right| \le \xi_2$, and ξ_2 is a continuous function.

Further, we obtain

$$y_2\dot{y}_2 \le -\frac{y_2}{\tau_2} + |y_2|\xi_2 \le -\frac{y_2}{\tau_2} + y_2^2 + \frac{1}{4}\xi_2^2 \quad (14)$$

Step i ($2 \le i \le n-1$)

The time derivative of z_i is

$$\dot{z}_i = f_i(\bar{s}_{i+1}) + s_{i+1} - \dot{\omega}_i \quad (15)$$

Therefore, the derivative of V_{z_i} with respect to t is

$$\begin{aligned} \dot{V}_{z_i} &= z_i[z_{i+1} + y_{i+1} + \alpha_i + h_i(Z_i)] - 3\frac{1}{4}z_i^2 \\ &= z_i[z_{i+1} + y_{i+1} + \alpha_i + W_{h_i}^{*T} S_i(Z_i) + \varepsilon_{hi}(Z_i)] - 3\frac{1}{4}z_i^2 \\ &\le z_i[z_{i+1} + y_{i+1} + \alpha_i] + \frac{1}{2a_i^2} z_i^2 \theta_i \|S_i(Z_i)\|^2 \\ &\quad + \frac{a_i^2}{2} + z_i \varepsilon_{hi}(Z_i) - 3\frac{1}{4}z_i^2 \end{aligned} \quad (16)$$

where $h_i(Z_i) = f_i(\bar{s}_{i+1}) - \dot{\omega}_i + 3\frac{1}{4}z_i$, and $a_i > 0$ is a design constant.

Construct the virtual control α_i as follows:

$$\alpha_i = -k_i z_i^{2\beta-1} - \frac{z_i}{2a_i^2}\hat{\theta}_i \|S_i(Z_i)\|^2 \quad (17)$$

where k_i is a positive design constant that we will choose later.

The adaptive law of the parameter $\hat{\theta}_i$ is determined by (10) for i.

Define ω_{i+1} in such a way that

$$\tau_{i+1}\dot{\omega}_{i+1} + \omega_{i+1} = \alpha_i, \omega_{i+1}(0) = \alpha_i(0),$$

where τ_{i+1} is a positive design constant.

$$s_{i+1} = z_{i+1} + y_{i+1} - k_i z_i^{2\beta-1} - \frac{z_i}{2a_i^2}\hat{\theta}_i \|S_i(Z_i)\|^2 \quad (18)$$

Using young's inequality, we obtain

$$\dot{V}_{z_i} \le -k_i z_i^{2\beta} - \frac{z_i^2 \tilde{\theta}_i \|S_i(Z_i)\|^2}{2a_i^2} + \frac{z_{i+1}^2}{4} + \frac{y_{i+1}^2}{4} + \frac{a_i^2}{2} + z_i\eta_i - 1\frac{1}{4}z_i^2 \quad (19)$$

where continuous function η_i satisfies $|\varepsilon_i(Z_i)| \le \eta_i$.

From young's inequality, we have

$$|z_i|\eta_i \le z_i^2 + \frac{1}{4}\eta_i^2 \quad (20)$$

Therefore, we obtain

$$\dot{V}_{z_i} \le -k_i z_i^{2\beta} - \frac{z_i^2 \tilde{\theta}_i \|S_i(Z_i)\|^2}{2a_i^2} + \frac{z_{i+1}^2}{4} + \frac{y_{i+1}^2}{4} + \frac{a_i^2}{2} + \frac{1}{4}\eta_i^2 - \frac{1}{4}z_i^2 \quad (21)$$

Then, one has

$$y_{i+1}\dot{y}_{i+1} \le -\frac{y_{i+1}}{\tau_{i+1}} + y_{i+1}^2 + \frac{1}{4}\xi_{i+1}^2 \quad (22)$$

Step n: The control law u will be design in this step.

The time derivative of z_n is

$$\dot{z}_n = f_n(\bar{s}_n) + k_n(s_n)\varphi_n Q(u) - \dot{\omega}_n \quad (23)$$

Therefore, the derivative of V_{z_n} with respect to t is $\dot{V}_{z_n} = z_n[f_n(\bar{s}_n) + k_n(s_n)\varphi_n(mu(t) + d(t)) - \dot{\omega}_n]$, since $d(t) \le \rho$, then we obtain

$$\dot{V}_{z_n} \le z_n k_n(s_n)\varphi_n mu + \frac{g_0 z_n^2 \theta_n \|S_n(Z_n)\|^2}{2a_n^2} + \frac{a_n^2}{2g_0} + \varepsilon_{hn}(Z_n) - 1\frac{1}{4}z_n^2 \quad (24)$$

where $a_n > 0$ is a design constant and $g_0 > 0$ we will give later, and

$$h_n(Z_n) = f_n(\bar{s}_n) - \dot{\omega}_n + k_n(s_n)\varphi_n\rho + 1\frac{1}{4}z_n, Z_n = [\bar{s}_n^T, z_n, \dot{\omega}_n]^T \in R^{n+2}.$$

Design the control law u as follows:

$$u = \frac{1}{m\varphi_n}[-k_n z_n^{2\beta-1} - \frac{z_n}{2a_n^2}\hat{\theta}_n \|S_n(Z_n)\|^2] \quad (25)$$

$\hat{\theta}_n$ is the estimate of θ_n, the function as

$$\dot{\hat{\theta}}_n = \gamma_n[\frac{1}{2a_n^2} z_n^2 \|S_n(Z_n)\|^2 - \sigma_n\hat{\theta}_n] \quad (26)$$

Volume 8, Issue 7, pp. 114-118, 2024.

International Journal of Scientific Engineering and Science
ISSN (Online): 2456-7361

Let $\frac{2}{k_{cn}} = g_0$, then we have

$$\dot{V}_{z_n} \le -g_0 k_n z_n^{2\beta} - \frac{g_0 z_n^2 \hat{\theta}_n \|S_n(Z_i)\|^2}{2a_n^2} + \frac{g_0 z_n^2 \theta_n \|S_n(Z_i)\|^2}{2a_n^2} + \frac{a_n^2}{2g_0} + z_n \eta_n - 1\frac{1}{4} z_n^2 \quad (27)$$

where continuous function η_n satisfies $|\varepsilon_{hn}(Z_n)| \le \eta_n$.

Using young's inequality, we have

$$|z_n| \eta_n \le z_n^2 + \frac{1}{4}\eta_n^2 \quad (28)$$

From the above, it can be concluded that

$$\dot{V}_{z_n} \le -g_0 k_n z_n^{2\beta} - \frac{g_0 z_n^2 \tilde{\theta}_n \|S_n(Z_i)\|^2}{2a_n^2} + \frac{a_n^2}{2g_0} - \frac{1}{4} z_n + \frac{1}{4}\eta_n^2 \quad (29)$$

Theorem 1 Consider the closed-loop system consisting of system (1) under Assumption 1, the controller (25), and adaption law (10). For bounded initial conditions, satisfying $V_n(0) \le p$, $k_{c1} \le B_1$, and $x_i(0) \in \Omega_{x_i}$, there exist constants $k_i > 0, \tau_i > 0, \gamma_i > 0, \sigma_i > 0$, such that the overall closed-loop neural control system is SGPFS in the sense that all of the signals in the closed-loop system are finite-time bounded, and $x_i \in \Omega_{x_i}, \forall t \ge 0$,i.e., the full state constraints are never violated, in addition, k_i and τ_i satisfy

$$\begin{cases} k_i \ge \frac{\alpha_0}{2} 2^\beta, k_n \ge \frac{\alpha_0}{2g_0} 2^\beta, i = 1, \cdots, n-1 \\ \frac{1}{\tau_i} \ge 1\frac{1}{4} + \frac{\alpha_0}{2} \\ \alpha_0 = \min\{\gamma_1\sigma_1, \cdots, \gamma_n\sigma_n\} \end{cases} \quad (30)$$

Proof. Consider the overall Lyapunov function candidate as follows:

$$V = V_n = \sum_{i=1}^{n} [V_{zi} + \frac{1}{2\gamma_i} g_{i0} \tilde{\theta}_i^2] + \frac{1}{2}\sum_{i=1}^{n-1} y_{i+1}^2 \quad (31)$$

Differentiating $V(t)$ with respect to time t leads to

$$\dot{V} = \sum_{i=1}^{n} [\dot{V}_{zi} + \frac{1}{\gamma_i}\tilde{\theta}_i \dot{\hat{\theta}}_i] + \sum_{i=1}^{n-1} y_{i+1}\dot{y}_{i+1} \quad (32)$$

Substituting (13), (14), (21), (22) and (29) into (32), and applying (10) and (26), it follows that

$$\dot{V} \le \sum_{i=1}^{n-1} -k_i z_i^{2\beta} + g_0 k_n + \sum_{i=1}^{n-1} [-\frac{y_{i+1}^2}{\tau_{i+1}} + 1\frac{1}{4} y_{i+1}^2 + \frac{1}{4}\xi_{i+1}^2] + \sum_{i=1}^{n-1} \frac{a_i^2}{2g_{i0}} + \frac{a_n^2}{2g_0} + \sum_{i=1}^{n} \frac{1}{4}\eta_i^2 + \sum_{i=1}^{n} [-\sigma_i \tilde{\theta}_i \hat{\theta}_i] \quad (33)$$

If $V = V_n = p$, then $\eta_i^2 \le H_i^2$ and $\xi_{i+1}^2 \le M_{i+1}^2$, By completion of squares, we have

$$-\sigma_i \tilde{\theta}_i \hat{\theta} = -\sigma_i \tilde{\theta}_i (\tilde{\theta}_i + \theta_i) \le \sigma_i (-\frac{\tilde{\theta}_i^2}{2} + \frac{\theta_i^2}{2}) \quad (34)$$

Now we apply lemma 2 and Lemma 3, one has

$$\dot{V} \le -\alpha V^\beta + \mu \quad (35)$$

where $\alpha = \min\{\alpha_0, \alpha_0^\beta\}$,

$$\mu = \sum_{i=1}^{n} \frac{1}{4}\eta_i^2 + \sum_{i=1}^{n-1} \frac{a_i^2}{2} + \frac{a_n^2}{2g_0} + \sum_{i=1}^{n} -\gamma_i\sigma_i \frac{1}{2\gamma_i}\tilde{\theta}_i^2 + \sum_{i=1}^{n} \frac{1}{2}\sigma_i\theta_i^2 + 2(1-\beta)l .$$

It means that all the signals in the closed-loop system are SGPFS. Therefore, z_i, y_i and $\hat{\theta}_i$ are finite time bounded. s_i, α_i, ω_{i+1} are also finite time bounded.

IV. SIMULATION RESULTS

Consider a nonlinear system, the dynamic equation is given as follows:

$$\begin{cases} \dot{x}_1 = 0.1x_1^2 + x_2 \\ \dot{x}_2 = 0.2\sin(x_1) + x_1 + 2u \\ y = x_1 \end{cases} \quad (37)$$

For conducting the simulation, the initial conditions are $x_1(0) = 0.13$, $x_2(0) = 1.43$, $\tau_2 = 0.01$, $\theta_1(0) = 0.1$, $\theta_2(0) = 0.3$, $\omega_2(0) = 0.1$.

The reference signal is $y_d = 0.3\cos(0.57t + 0.6) - 0.24$, and the states are constrained in the regions $|x_1| < 0.16$ and $|x_2| < 1.5$. The parameters are selected as $k_1 = 4$, $k_2 = 15$, $a_1 = 1$, $a_2 = 1$, $\sigma_1 = \sigma_2 = 0.01$, $\gamma_1 = 50$, $\gamma_2 = 30$, $b_r = 0.3$, $b_l = 0.5$, $m_r = m_l = 0.8$, $l = 0.5$, $\tau_2 = 0.01$, $\beta = 99/101$.

International Journal of Scientific Engineering and Science
Volume 8, Issue 7, pp. 114-118, 2024. ISSN (Online): 2456-7361

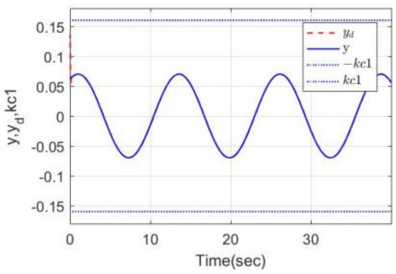

Fig. 1. Output y , desired trajectory y_d and constraints $kc1$

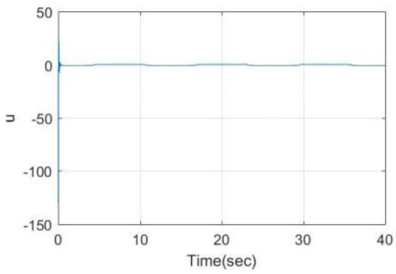

Fig. 2. Control law u

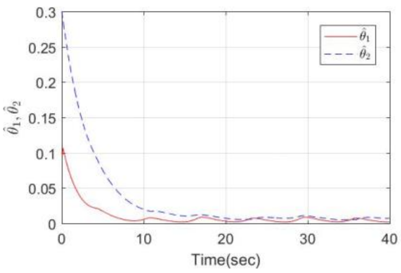

Fig. 3. The curve of $\hat{\theta}_1$ and $\hat{\theta}_2$

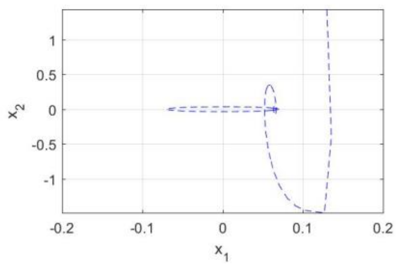

Fig. 4. Phase portrait of states x_1 , x_2

The simulation results are shown in the Fig. 1–4. From above Figures, we can see that the all states abide by extended constraint conditions, and the control objective can be well implemented. Moreover, all signals in systems are bounded.

V. CONCLUSION

Adaptive finite-time tracking control for nonlinear systems subject to full state constraints and dead-zone is studied in this paper. Base on DSC, control, a novel adaptive finite time tracking control is proposed by utilizing the finite-time stability theory and NM. All the signals in the close-loop system are proved to be SGPFB and state constraints have not been triggered. The simulation further verified the effectiveness of the proposed finite time control strategy.

ACKNOWLEDGMENT

This work was partially supported by the Natural Science Key Research Project for Higher Education Institutions of Anhui Province (2022AH051054).

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