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Adaptive Control for a Pneumatic Muscle Joint System With Saturation Input

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ABSTRACT Pneumatic muscle is a relatively new pneumatic component in some precise and flexible control systems and such systems are needed to achieve a higher controlling performance. However, the existence of practical uncertainties will make it hard to achieve a higher control accuracy and better performance. In this paper, the adaptive control problem for the pneumatic muscle joint system with input saturation, external disturbance and modeling errors is investigated. The auxiliary signals r_1, r_2 and function ψ_{sgn} as an approximation of $sign(\cdot)$ function is introduced to deal with the unknown saturation and uncertainties caused by modeling errors. Then an adaptive control scheme is proposed by using these auxiliary signals and functions. Finally, simulation studies are used to verify the effectiveness of the proposed control scheme.

INDEX TERMS Pneumatic muscle joint system, external disturbance, modeling errors, backstepping, input saturation.

I. INTRODUCTION

Pneumatic muscle [1], [2], also known as pneumatic muscle actuator, is a relatively new pneumatic component in some precise and flexible control systems, such as robotic knee prosthesis [3], virtual reality, and bionic robot, etc. There are several good characteristics of the pneumatic muscle in practice, for example, light-weight, low cost, high power-weight ratio, and high power volume ratio. In a word, the most important advantage is that pneumatic muscle is similar to human skeletal muscle. Therefore, the pneumatic muscle has extensive application prospects in the fields of rehabilitation medicine, virtual reality, and bionic robot, etc. However, uncertainties of the pneumatic muscle systems caused by non-smooth nonlinearity and gas compressibility [1] may result its controlling becoming more complicated. Then higher control accuracy is difficult to be achieved.

As we all know, all sorts of uncertainties [4]–[27] are common to the practical system. Such uncertainties including unknown parameters [4]–[7], [10], [13]–[27], external disturbance [4]–[7], [10] and modeling errors [8], [9] may lead to the degradation of system performance. To guarantee good performance, uncertainties must be fully considered in the controller design and stability analysis. To deal with linearized parameters, there are some advantages to using adaptive control approaches. The update laws can be designed to realize the online estimation of unknown parameters. Especially, the estimation laws can be adjusted automatically to the new parameter value when the value of parameter changes suddenly. This sudden change is usually caused by unknown actuator failures [11]–[27] during the operation of systems. To compensate for the uncertainties caused by external disturbance, we usually assume that such disturbance is bounded by an unknown positive constant. By estimating this upper bound, the disturbance can be restrained effectively. Unknown modeling errors are difficult to be handled compared with these above two uncertainties. The neural-networks method is popular to compensate for the uncertainties caused by modeling errors [28]. Some inequalities can also be used to restrain modeling error when its upper bound being a known function.

In addition to the above uncertainties, input saturation [4], [6] is inevitable in a pneumatic muscle joint system. The existence of saturation which is unknown due to the unknown parameters may reduce the system performance. Therefore, to obtain the high precision control performance unknown saturation and above uncertainties can not be ignored in controller design and stability analysis. In recent years, several results have been proposed about the control design for systems with non-smooth nonlinear inputs [4]–[9].

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By using the linear approximation of backlash-like hysteresis, a control scheme have been proposed in [4], [5] and [27]. Considering unknown saturation, an approximation has been constructed in [6] which must be handled by fuzzy and NN techniques. How to compensate for the effect caused by unknown saturation by traditional backstepping is always an important problem. To solve such a problem, we consider the adaptive control for pneumatic muscle joint system with unknown parameters, external disturbances and modeling errors in this paper. Furthermore, input saturation is also fully considered in the controller design. We use different techniques to do with different uncertainties. The auxiliary signals are introduced to reduce the influence of unknown saturation input nonlinearity. The main contributions of this paper can be summarized as follows: (I) The control problem is investigated for pneumatic muscle joint systems with input saturation, external disturbance, unknown modeling errors, and parameters are fully considered in the controller design. An adaptive control scheme is proposed to guarantee system performance; (II) In contrast to existing results, we consider all sorts of uncertainties. The auxiliary signals r_1, r_2 are introduced to deal with the unknown saturation; (III) To improve system performance, we introduce function ψ_{sgn} as an approximation of $sign(\cdot)$ in controller design which helps to compensate for the effects caused by modeling errors.

The paper is organized as follows: Section II describes controlled system model with unknown saturation, unknown external disturbance and unknown modeling errors. Section III presents the designed adaptive controller and analysis of the closed-loop system. Simulation results are given in Section IV to verify the effectiveness of the proposed control scheme. Finally, the paper is concluded in Section V.

II. PROBLEM STATEMENT

The force generated by the pneumatic muscle and the pressure value of the pneumatic muscle can be expressed by the following equations [2].

$$\begin{aligned} F_1(t) &= P_1(t)(C_1\varepsilon_1(t)^2 + C_2\varepsilon_1(t) + C_3) + C_4 \\ F_2(t) &= P_2(t)(C_1\varepsilon_2(t)^2 + C_2\varepsilon_2(t) + C_3) + C_4 \end{aligned} \tag{1}$$

where F_1, F_2 are the pulling forces on two pneumatic muscles. C_1, C_2, C_3, C_4 represent parameters in the mathematical model of aerodynamic muscles. $P_1(t)$ and $P_2(t)$ will be described in following equation (3). $\varepsilon_1, \varepsilon_2$ are the contraction rate of the pneumatic muscle and given as

$$\begin{aligned} \varepsilon_1(t) &= \varepsilon_0 + rl_0^{-1}\theta(t) \\ \varepsilon_2(t) &= \varepsilon_0 - rl_0^{-1}\theta(t) \end{aligned} \tag{2}$$

where ε_0 and l_0 represent the initial contraction rate and initial length of the pneumatic muscle, respectively. $\theta(t)$ is the rotation angle of the pneumatic muscle joint. Clearly, we have

$$\begin{aligned} P_1(t) &= P_0 + \triangle P(t) = k_0u_0 + k_uu(t) \\ P_2(t) &= P_0 - \triangle P(t) = k_0u_0 - k_uu(t) \end{aligned} \tag{3}$$

where k_0 is the proportionality factor. k_u is the voltage coefficient. u_0 is the initial voltage. P_0 is the initial pressure of the pneumatic muscle. $\triangle P(t)$ is the pressure change of the pneumatic muscle. $P_1(t)$ and $P_2(t)$ are the pressure values of the pneumatic muscle.

According to the dynamic model of the Lagrangian form of the pneumatic muscle joint, the following equation can be obtained

$$\begin{aligned} T(t) &= J\ddot{\theta}(t) + b_v\dot{\theta}(t) \\ &= F_1(t)b_1 - F_2(t)b_2 + \vartheta(t) \end{aligned} \tag{4}$$

where J is the moment of inertia of the pneumatic muscle joint. b_v is the damping coefficient of the pneumatic muscle joint system. $\vartheta(t)$ represents unknown terms such as external disturbances and unmodeled dynamics of the pneumatic muscle system. b_1, b_2 represents the radius of the pneumatic muscle joint.

In the pneumatic muscle joint platform targeted in this article, the joint radius is the gear radius of the joint, $b_1 = b_2 = r$. With (1) (2) (3) and (4), we have

$$\begin{aligned} T(t) &= k_0u_0r(4C_1\varepsilon_0rl_0^{-1} + 2C_2rl_0^{-1})\theta(t) \\ &\quad + k_0k_ur(2C_1\varepsilon_0^2 + 2C_1(r\theta(t)l_0^{-1})^2 \\ &\quad + 2C_2\varepsilon_0 + 2C_3)u(t) + \vartheta(t) \end{aligned} \tag{5}$$

By simplifying the aerodynamic muscle model, we have

$$\begin{aligned} \ddot{\theta}(t) &= -\frac{b_v}{J}\dot{\theta}(t) + \frac{2k_0u_0r^2(2C_1\varepsilon_0 + C_2)l_0^{-1}}{J}\theta(t) \\ &\quad + \frac{2k_0k_ur(C_1\varepsilon_0^2 + C_2\varepsilon_0 + C_3)}{J}u(t) + d(t) \end{aligned} \tag{6}$$

In order to facilitate the design of the controller, the system stats are selected as follows

$$\begin{cases} x_1(t) = \theta(t) \\ x_2(t) = \dot{\theta}(t) \end{cases} \tag{7}$$

Then the system model can be rewritten as

$$\begin{aligned} \dot{x}_1(t) &= x_2(t) \\ \dot{x}_2(t) &= d_1x_1(t) + d_2x_2(t) + \frac{\vartheta(t)}{J} + b_0u(t) \\ y &= x_1 \end{aligned} \tag{8}$$

where y is the output signal and

$$\begin{aligned} b_0 &= \frac{2k_0k_ur(C_1\varepsilon_0^2 + C_2\varepsilon_0 + C_3)}{J} \\ d_1 &= \frac{2k_0u_0r^2(2C_1\varepsilon_0 + C_2)l_0^{-1}}{J} \\ d_2 &= -\frac{b_v}{J} \end{aligned} \tag{9}$$

We let $\eta(t,x) = \frac{\vartheta(t)}{J}$ representing all unknown modeling errors and external disturbance. Then the controlled system model can be rewritten as

$$\begin{aligned} \dot{x}_1(t) &= x_2(t) \\ \dot{x}_2(t) &= d_1x_1(t) + d_2x_2(t) + b_0u(t) + \eta(x,t) \\ y(t) &= x_1(t) \end{aligned} \tag{10}$$

where x_1, x_2, y and u are system states, output and input. d_1, d_2 are unknown constants and b_0 is a known parameter.

Remark 1: As we all know, uncertainties including unknown parameters, modeling errors and disturbance are inevitable in practice. So we use $\eta(x, t)$ representing all unknown modeling errors and external disturbance. $\eta(x, t)$ is an unknown nonlinear function and such that

$$|\eta(x, t)| \leq D + \delta(x, t) \tag{11}$$

where $D > 0$ is an unknown constant and $\delta(x, t)$ is a known function. D will be estimated by designing the estimator. Modeling error is handled by introducing $\delta(x, t)\psi_{sgn}(\frac{z_2\delta(x,t)}{\epsilon})$ in α which will be shown in (26). Then we use the inequality amplification technique given in (29) to restrain the unknown effect modeling errors.

Consider the following saturation input

$$u(v) = sat(v) = \begin{cases} u_M & v > u_M \\ v & -u_M \leq v \leq u_M \\ -u_M & v < -u_M \end{cases} \tag{12}$$

where $u_M > 0$ is an unknown constant. $u(v)$ is the control input which will act on system and v is the control signal which will be designed.

Remark 2: Actually, saturation input is the most common non-smooth nonlinearity of actuators in practical systems. In pneumatic muscle joint system, due to the limitation of inflation catheter we must consider the saturation in the controller design and stability analysis.

With the saturation model (12), the controlled system is reorganized as

$$\begin{aligned} \dot{x}_1(t) &= x_2(t) \\ \dot{x}_2(t) &= d_1x_1(t) + d_2x_2(t) + b_0u(v) + \eta(x, t) \\ y(t) &= x_1(t) \end{aligned} \tag{13}$$

The above mathematical model is a triangular system. Backstepping approach will be used to design the adaptive controller. To propose the controller design the following assumptions are made.

Assumption 1: The reference signal y_r and its *i-th*$(i = 1, 2)$ order derivatives are continuous and bounded.

III. DESIGN OF ADAPTIVE CONTROLLERS

To deal with the uncertainties caused by unknown saturation, the following auxiliary signals r_1, r_2 are introduced.

$$\begin{aligned} \dot{r}_1 &= r_2 - C_{k1}r_1 \\ \dot{r}_2 &= -C_{k2}r_2 + b_0\triangle u \end{aligned} \tag{14}$$

where $\triangle u = u - v$ is the error between the output and input of saturation actuator. C_{k1}, C_{k2} are positive constants. To proceed the controller design, we first perform a coordinate transformation.

$$\begin{aligned} z_1 &= y - y_r - r_1 \\ z_2 &= x_2 - \alpha_1 - \dot{y}_r - r_2 \end{aligned} \tag{15}$$

The above coordinate transformations are different from the traditional backstepping technique. To characterize the effect caused by saturation input, signals r_1 and r_2 generated by Δu have been introduced in z_1 and z_2, respectively.

As we all know, the nonlinear approximation shown in [6] and inverse can be used to compensate for the effect of unknown saturation input. Fuzzy and NN technique are usually used when we use a nonlinear function to approximate saturation. Inverse control can not be used in backsteppting control design due to the inverse being non-smooth. So an auxiliary system (14) was introduced to overcome such difficulties.

Step 1: We start with the first equation of system (13) by considering x_2 as a virtual control variable. The derivative of error z_1 is

$$\dot{z}_1 = x_2 - \dot{y}_r - r_2 + C_{k1}r_1 \tag{16}$$

Considering the Lyapunov function V_1 as

$$V_1 = \frac{1}{2}z_1^2 \tag{17}$$

Then the derivative of V_1 is

$$\begin{aligned} \dot{V}_1 &= z_1\dot{z}_1 \\ &= z_1(z_2 + \alpha_1 + \dot{y}_r + r_2 - \dot{y}_r - r_2 + C_{k1}r_1) \\ &= z_1(z_2 + \alpha_1 + C_{k1}r_1) \end{aligned} \tag{18}$$

We choose the virtual control law α_1 as

$$\alpha_1 = -C_1z_1 - C_{k1}r_1 \tag{19}$$

where C_1 is a positive constant. Then we have

$$\dot{V}_1 = z_1z_2 - C_1z_1^2 \tag{20}$$

Step 2: From (13)-(15) the derivative of z_2 is

$$\dot{z}_2 = \dot{x}_2 - \dot{\alpha}_1 - \dot{\dot{y}}_r - \dot{r}_2 \tag{21}$$

$$= d_1x_1(t) + d_2x_2(t) + \eta(t, x) + b_0v - \dot{\alpha}_1 - \ddot{y}_r + C_{k2}r_2 \tag{22}$$

Then

$$\begin{aligned} z_2\dot{z}_2 &= z_2(d_1x_1(t) + d_2x_2(t) \\ &\quad + b_0v - \dot{\alpha}_1 - \ddot{y}_r + C_{k2}r_2) + z_2\eta(t, x) \end{aligned} \tag{23}$$

$$\begin{aligned} &\leq z_2(d_1x_1(t) + d_2x_2(t) + b_0v - \dot{\alpha}_1 \\ &\quad - \ddot{y}_r + C_{k2}r_2) + |z_2|D + |z_2\delta(t, x)| \end{aligned} \tag{24}$$

The control law and update laws are designed as follows:
control law

$$v = \bar{\alpha} \tag{25}$$

and

$$\begin{aligned} \bar{\alpha} = &-z_1 - C_2z_2 - \hat{d}_1x_1 - \hat{d}_2x_2 + \ddot{y}_r - sign(z_2)\hat{D} \\ &-C_{k2}r_2 + \dot{\alpha}_1 - \delta(x, t)\psi_{sgn}(\frac{z_2\delta(x, t)}{\epsilon}) \end{aligned} \tag{26}$$

where C_2 and ϵ are positive constants. $\psi_{sgn}(\cdot)$ is a smooth function and constructed as

$$\psi_{sgn}(\xi) = \begin{cases} \frac{\xi}{|\xi|}, & |\xi| \geq \delta_0 \\ \frac{\xi}{(\delta_0^2 - \xi^2)^2 + |\xi|}, & |\xi| < \delta_0 \end{cases} \tag{27}$$

where δ_0 is a positive design parameter.

update law

$$\begin{aligned} \dot{\hat{d}}_1 &= z_2 \eta_{d_1} x_1 - \eta_{d1} l_{d1}(\hat{d}_1 - d_{10}) \\ \dot{\hat{d}}_2 &= z_2 \eta_{d_2} x_2 - \eta_{d2} l_{d2}(\hat{d}_2 - d_{20}) \\ \dot{\hat{D}} &= \eta_D |z_2| - \eta_D l_D(\hat{D} - D_0) \end{aligned} \tag{28}$$

where $\eta_{d_1}, \eta_{d_2}, \eta_D, l_{d1}, l_{d2}, l_D, d_{10}, d_{20}, D_0$ are positive design parameters.

Remark 3: To guarantee the system stability, design parameters $l_{d1}, l_{d2}, l_D, d_{10}, d_{20}, D_0$ are introduced in the proposed adaptive control scheme. Especially, terms $\eta_{d1} l_{d1}(\hat{d}_1 - d_{10})$, $\eta_{d2} l_{d2}(\hat{d}_2 - d_{20})$, $\eta_D l_D(\hat{D} - D_0)$ in update laws of unknown parameters can guarantee the exponential convergence of the Laypunov function which will be shown in the next section.

IV. STABILITY ANALYSIS

We now establish the boundedness of all signals in the closed loop system. The following theorem about adaptive control of pneumatic muscle joint system with saturation input can be achieved.

Theorem 1: Considering pneumatic muscle joint system shown in (6), with saturation input (12), an adaptive controller with control law (25)-(26) and the update laws (28), and under Assumption 1, all signals of the closed-loop system are bounded.

Proof: Firstly, the Lemma 1 is introduced as follows:

Lemma 1 [29]: For any $\epsilon > 0$, $\psi_{sgn}(\xi)$ satisfies

$$|\xi| - \xi \psi_{sgn}(\frac{\xi}{\epsilon}) \leq \epsilon \delta_0, \quad \forall \epsilon > 0 \tag{29}$$

Clearly, when $\frac{|\xi|}{\epsilon} \geq \delta_0$, we can easily get $|\xi| - \xi\psi_{sgn}(\frac{\xi}{\epsilon}) = 0$. Then the above inequality is achieved. When $\frac{|\xi|}{\epsilon} < \delta_0$, we have

$$\begin{aligned} |\xi| - \xi \psi_{sgn}(\frac{\xi}{\epsilon}) &= \frac{|\xi|(\delta_0^2 - \xi^2)^2}{(\delta_0^2 - \xi^2)^2 + |\xi|} \\ &\leq \frac{|\xi|(\delta_0^2 - \xi^2)^2}{(\delta_0^2 - \xi^2)^2} \\ &\leq \epsilon \delta_0 \end{aligned} \tag{30}$$

We chose the Lyapunov function V_2 as

$$V_2 = V_1 + \frac{1}{2} z_2^2 + \frac{1}{2\eta_{d_1}} \tilde{d}_1^2 + \frac{1}{2\eta_{d_2}} \tilde{d}_2^2 + \frac{1}{2\eta_D} \tilde{D}^2 \tag{31}$$

The derivative of the Lyapunov function V_2 satisfies

$$\begin{aligned} \dot{V}_2 &= z_1 z_2 - C_1 z_1^2 + z_2 \dot{z}_2 \\ &\quad - \frac{1}{\eta_{d_1}} \tilde{d}_1 \dot{\hat{d}}_1 - \frac{1}{\eta_{d_2}} \tilde{d}_2 \dot{\hat{d}}_2 - \frac{1}{\eta_D} \tilde{D} \dot{\hat{D}} \\ &\leq z_1 z_2 - C_1 z_1^2 + z_2(d_1 x_1(t) + d_2 x_2(t) + b_0 v \\ &\quad - \dot{\alpha}_1 - \ddot{y}_r + C_{k2} r_2) + |z_2| D + |z_2 \delta(t, x)| \\ &\quad - \frac{1}{\eta_{d_1}} \tilde{d}_1 \dot{\hat{d}}_1 - \frac{1}{\eta_{d_2}} \tilde{d}_2 \dot{\hat{d}}_2 - \frac{1}{\eta_D} \tilde{D} \dot{\hat{D}} \end{aligned} \tag{32}$$

From (25), the $\dot{V}_2$ is

$$\begin{aligned} \dot{V}_2 &\leq -C_1 z_1^2 - C_2 z_2^2 + z_2 \tilde{d}_1 x_1 + z_2 \tilde{d}_2 x_2 - |z_2| \tilde{D} \\ &\quad - \frac{1}{\eta_{d_1}} \tilde{d}_1 \dot{\hat{d}}_1 - \frac{1}{\eta_{d_2}} \tilde{d}_2 \dot{\hat{d}}_2 - \frac{1}{\eta_D} \tilde{D} \dot{\hat{D}} + |z_2 \delta(x, t)| \\ &\quad - z_2 \delta(x, t) \psi_{sgn}(\frac{z_2 \delta(x, t)}{\epsilon}) \\ &= -C_1 z_1^2 - C_2 z_2^2 + \frac{\tilde{d}_1}{\eta_{d_1}}(z_2 \eta_{d_1} x_1 - \dot{\hat{d}}_1) \\ &\quad + \frac{\tilde{d}_2}{\eta_{d_2}}(z_2 \eta_{d_2} x_2 - \dot{\hat{d}}_2) + \frac{\tilde{D}}{\eta_D}(\eta_D |z_2| - \dot{\hat{D}}) \\ &\quad + |z_2 \delta(x, t)| - z_2 \delta(x, t) \psi_{sgn}(\frac{z_2 \delta(x, t)}{\epsilon}) \end{aligned} \tag{33}$$

Then with Lemma 1, we have

$$|z_2 \delta(x, t)| - z_2 \delta(x, t) \psi_{sgn}(\frac{z_2 \delta(x, t)}{\epsilon}) \leq \epsilon \delta_0 \tag{34}$$

So the derivative of V_2 is

$$\begin{aligned} \dot{V}_2 &\leq -C_1 z_1^2 - C_2 z_2^2 + \frac{\tilde{d}_1}{\eta_{d_1}}(z_2 \eta_{d_1} x_1 - \dot{\hat{d}}_1) \\ &\quad + \frac{\tilde{d}_2}{\eta_{d_2}}(z_2 \eta_{d_2} x_2 - \dot{\hat{d}}_2) + \frac{\tilde{D}}{\eta_D}(\eta_D |z_2| - \dot{\hat{D}}) \\ &\quad + \epsilon \delta_0 \end{aligned} \tag{35}$$

With update laws (28), we can get

$$\begin{aligned} \dot{V} \leq &- \sum_{i=1}^{2} c_i z_i^2 + \tilde{d}_1 l_{d1}(\hat{d}_1 - d_{10}) + \tilde{d}_2 l_{d2}(\hat{d}_2 - d_{20}) \\ &+ \tilde{D} l_D(\hat{D} - D_0) + \varepsilon \delta_0 \end{aligned} \tag{36}$$

With the following inequalities

$$\begin{aligned} l_{d1} \tilde{d}_1(\hat{d}_1 - d_{10}) &\leq -\frac{1}{2} l_{d1} \tilde{d}_1^2 + \frac{1}{2} l_{d1}(d_1 - d_{10})^2 \\ l_{d2} \tilde{d}_2(\hat{d}_2 - d_{20}) &\leq -\frac{1}{2} l_{d2} \tilde{d}_2^2 + \frac{1}{2} l_{d2}(d_2 - d_{20})^2 \end{aligned} \tag{37}$$

and

$$l_D \tilde{D}(\hat{D} - D_0) \leq -\frac{1}{2} l_D \tilde{D}^2 + \frac{1}{2} l_D(D - D_0)^2 \tag{38}$$

We have

$$\begin{aligned} \dot{V}_2 \leq &-C_1 z_1^2 - C_2 z_2^2 - \frac{1}{2} l_{d1} \tilde{d}_1^2 - \frac{1}{2} l_{d2} \tilde{d}_2^2 - \frac{1}{2} l_D \tilde{D}^2 \\ &- \frac{1}{2} l_\rho \tilde{\rho}^2 + \frac{1}{2} l_{d1}(d_1 - d_{10})^2 + \frac{1}{2} l_{d2}(d_2 - d_{20})^2 \\ &+ \frac{1}{2} l_D(D - D_0)^2 + \epsilon \delta_0 \end{aligned} \tag{39}$$

Namely

$$\dot{V}_2 \leq -C_1 z_1^2 - C_2 z_2^2 - \frac{1}{2} l_{d1} \tilde{d}_1^2 - \frac{1}{2} l_{d2} \tilde{d}_2^2 - \frac{1}{2} l_D \tilde{D}^2 + \Xi \tag{40}$$

where

$$\Xi = \frac{1}{2}l_{d1}(d_1 - d_{10})^2 + \frac{1}{2}l_{d2}(d_2 - d_{20})^2 + \frac{1}{2}l_D(D - D_0)^2 + \epsilon\delta_0 \quad (41)$$

So we can confirm z_1, z_2, $\tilde{d}_1$, $\tilde{d}_2$, $\tilde{D}$ are all bounded. Then all signals of the closed-loop system are bounded under the proposed control law (25)-(26) and update laws (28).

Let

$$V = z_1^2 + z_2^2 + \tilde{d}_1^2 + \tilde{d}_2^2 + \tilde{D}^2 \quad (42)$$

and

$$h^+ = max\{\frac{1}{2}, \frac{1}{2\eta_{d_1}}, \frac{1}{2\eta_{d_2}}, \frac{1}{2\eta_D}\}$$
$$h^- = min\{C_1, C_2, \frac{1}{2l_{d_1}}, \frac{1}{2l_{d_2}}, \frac{1}{2l_D}\}$$

From (40), we can get

$$\dot{V}_2 \leq -h^- V + \Xi \quad (43)$$

Then from (31), we have

$$V_2 \leq h^+ V \quad (44)$$

So we can get

$$\dot{V}_2 \leq -h^-(\frac{1}{h^+})V_2 + \Xi = -(\frac{h^-}{h^+})V_2 + \Xi$$

With (43), we have

$$V_2 \leq V_2(0)e^{-h^* t} + \frac{\Xi}{h^*}(1 - e^{-h^* t}) \quad (45)$$

Namely

$$V_2 \leq V_2(0) + \frac{\Xi}{h^*} \quad (46)$$

where $h^* = \frac{h^-}{h^+}$.

Remark 4: From (46), we can find that the size of the bound V_2 depends on the initial value $V_2(0)$ and $\frac{\Xi}{h^*}$. Considering that

$$||y - y_r - \lambda_1||_2 = ||z_1||_2 \leq 2(V_2(0) + \frac{\Xi}{h^*}) \quad (47)$$

The bound of $||z_1||_2$ which is related to tracking error can be adjusted by the following roads.

- The value of $\frac{\Xi}{h^*}$ depends on the design parameters $C_1, C_2, l_{d1}, l_{d2}, l_D, \delta_0, \epsilon, \eta_{d_1}, \eta_{d_2}, \eta_D, d_{10}, d_{20}, D_0$. By choosing the values of these design parameters $\frac{\Xi}{h^*}$, the bound of $||z_1||_2$ can be reduced.
- $V_2(0)$ represents the initial value of V_2 which includes $z_1(0), z_2(0), \tilde{d}_1(0), \tilde{d}_2(0), \tilde{D}(0)$. The bound of $||z_1||_2$ can be also reduced by setting up the initial values of $z_1(0), z_2(0), \tilde{d}_1(0), \tilde{d}_2(0), \tilde{D}(0)$.
- Note that signal λ_1 exists in z_1, so the bound of tracking error $|y - y_r|$ depends on the bound of λ_1. If $\Delta u \to 0$ as $t \to \infty$, we have $\lambda_1 \to 0$. Then the bound of tracking error depends only on the design parameters and initial values.

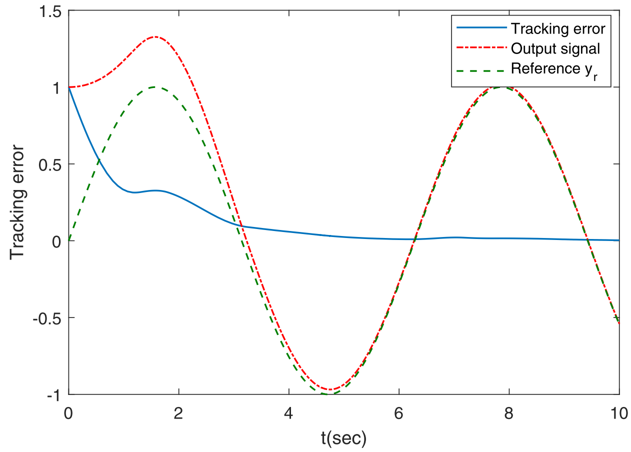

FIGURE 1. Tracking (Case 1).

V. SIMULATION STUDIES

We now apply the proposed control scheme to the following 2nd-order system described as

$$\dot{x}_1 = x_2$$
$$\dot{x}_2 = d_1x_1 + d_2x_2 + b_0u(v) + \eta(x, t)$$
$$y = x_1 \quad (48)$$

where x_1, x_2 are system states, y is the output signal. u is the output of the saturation actuator while v is the input signal. d_1, d_2 are unknown parameter. $\eta(x, t)$ is an unknown nonlinear function. The following two cases are considered.

Case 1: In this case, we take $d_1 = 0.1, d_2 = 0.65$, $b_0 = 2, u_M = 0.75$. The reference signal is $y_r = sint$ and unknown function $\eta(t)$ is taken as

$$\eta(x, t) = 0.2sin(x_1 + x_2)cost \quad (49)$$

In simulation, the design parameters can be chosen as: $c_1 = c_2 = 1, c_{k1} = c_{k2} = 1, \eta_{d1} = 1, \eta_{d2} = 1, \eta_D = 0.01$, $\eta_\rho = 1, l_{d1} = 0.1, l_{d2} = 0.1, l_D = 0.01, l_\rho = 0.1, \delta_0 = 0.1, \epsilon = 0.1, d_{10} = 0.2, d_{20} = 0.5, D_0 = 0.01, \rho_0 = 0.3$. The initial values are taken as: $x_1(0) = 2.5$, $x_2(0) = 0$, $\hat{\theta}(0) = 1$ and $\hat{D}(0) = 0$.

Fig.1 represents tracking error and the state x_2 is shown in Fig.2. Fig.3 shows the signal v which is designed by the proposed control law (25). After the change of saturation, the signal $u(t)$ is given in Fig.4. Fig.5 shows the auxiliary signals r_1 and r_2. Clearly, we can get that all signals of the systems are bounded under the controlling of the proposed control scheme.

To verify the effectiveness of the proposed control scheme to different reference signals, the following simulation is made. In this simulation, the reference signal is taken as $y_r = 0.5e^{-t}$. Design parameters is $c_{k1} = c_{k2} = 5$ and the other parameters, the initial values are the same as the above simulation. Fig.6 and Fig.7 represent tracking error and input signals, respectively. Clearly, we can get that the stability of the closed-loop systems can be guaranteed by the proposed control scheme with $y_r = 0.5e^{-t}$.

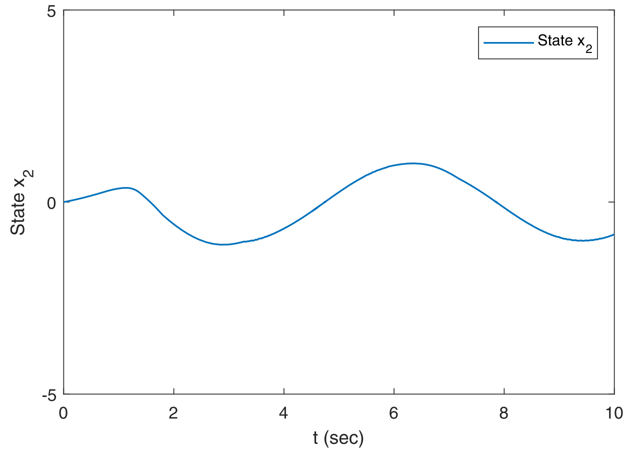

FIGURE 2. State x_2 (Case 1).

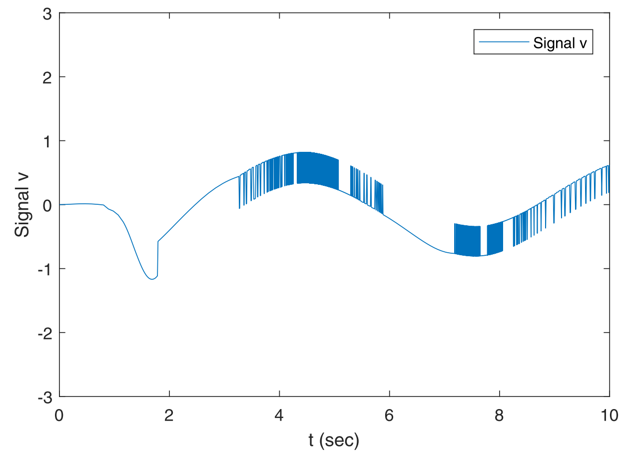

FIGURE 3. Signal v (Case 1).

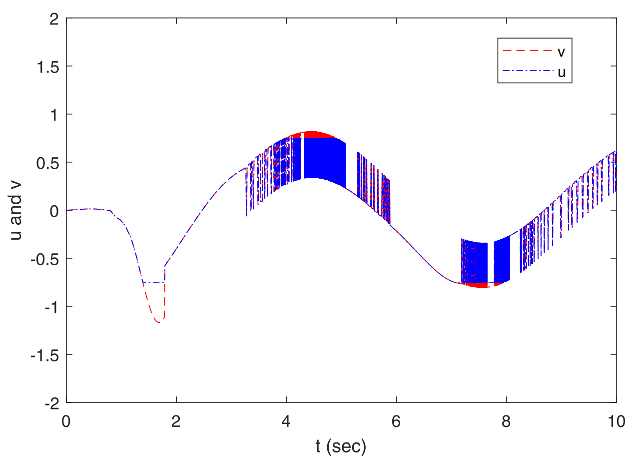

FIGURE 4. Input u (Case 1).

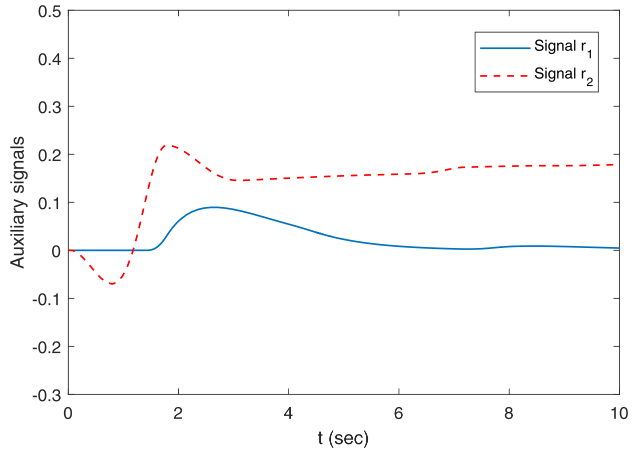

FIGURE 5. r_1 and r_2 (Case 1).

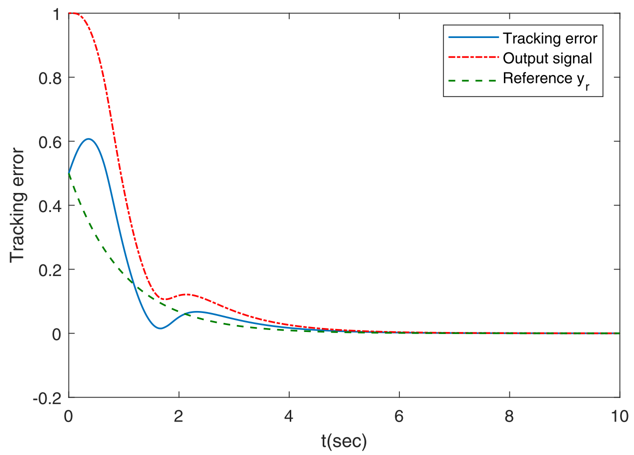

FIGURE 6. Tracking (Case 1, $y_r = 0.5e^{-t}$).

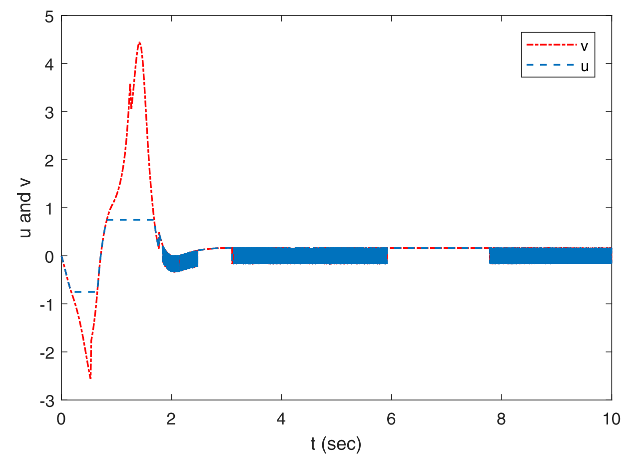

FIGURE 7. u and v (Case 1, $y_r = 0.5e^{-t}$).

Case 2: In this case, the mathematical model is chosen the same as model of simulation 1 shown in (48). The parameters are taken as $d_1 = 0.88, d_2 = 0.3, b_0 = 3$ and $\eta(x, t) = 0.1sin(x_2)$. Others parameters, reference signal and initial values are taken the same as simulation 1. Fig.8 represents tracking error and the signal u and v are shown in Fig.9. Clearly, the stability can be guaranteed in this simulation.

Furthermore, to reference signal $y_r = 0.5e^{-t}$, the simulation results including tracking errors and input u and v are shown in Fig.10 and Fig.11, respectively. All design

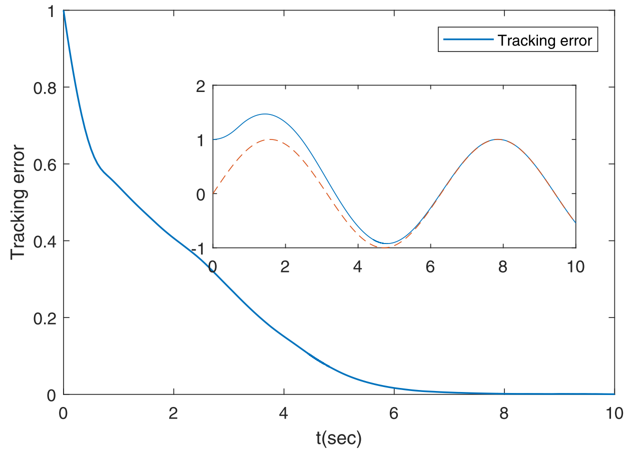

FIGURE 8. Tracking (Case 2).

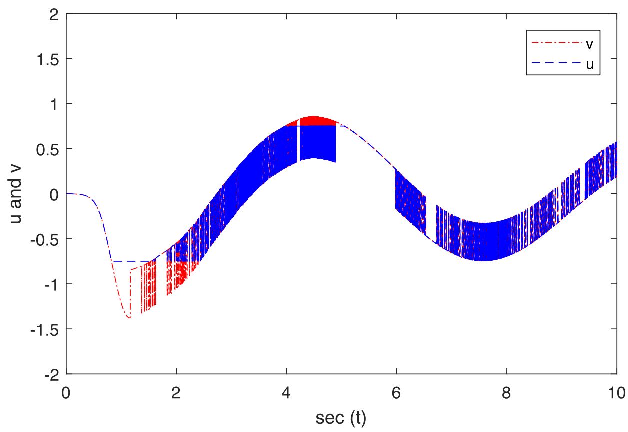

FIGURE 9. *u* and *v* (Case 2).

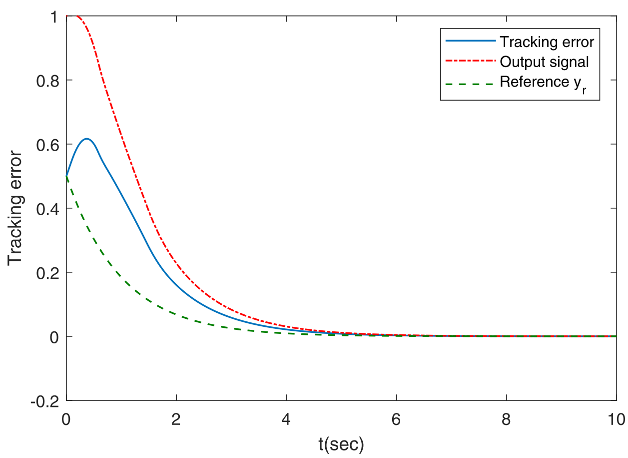

FIGURE 10. Tracking (Case 2, $y_r = 0.5e^{-t}$).

parameters and initial values are the same as case 2 except for $c_{k1} = c_{k2} = 5$. The stability is also guaranteed by the proposed control law.

Based on the simulation results including simulation 1 and simulation 2 shown in Fig1.-Fig.7 and Fig.8-Fig.11, respectively, we can obtain that the adaptive control scheme does not depend on the unknown system parameters d_1 and d_2.

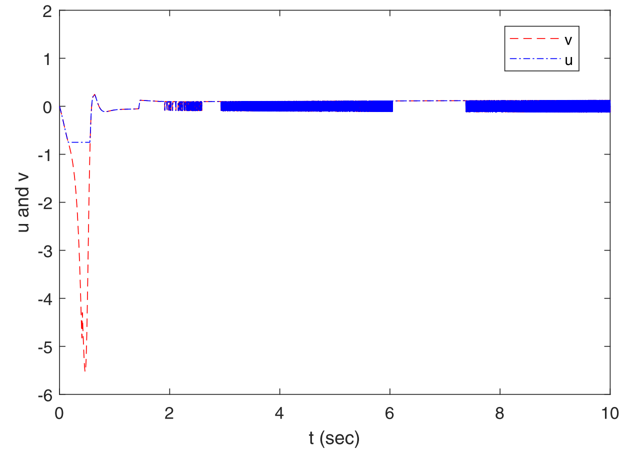

FIGURE 11. *u* and *v* (Case 2, $y_r = 0.5e^{-t}$).

Furthermore, the adaptive controller is robust to different parameter d_1, d_2, b_0, and external disturbance $\eta(t, x)$.

From Fig.4, Fig.7, Fig.9 and Fig.11, we can see that the denser phenomenon of the controller signal exists in our simulations. Such phenomenon may be caused by the discontinuous control signal u due to the estimation term $sign(z_2)\hat{D}$.

VI. CONCLUSION

In this paper, The control problem is investigated for pneumatic muscle joint system with unknown input saturation, external disturbance, and modeling errors. The uncertainties caused by unknown input saturation, external disturbance, modeling errors and unknown parameters have been compensated by the proposed adaptive control law and update laws of parameters. Finally, simulation studies are used to verify the effectiveness of the proposed control scheme. In our future work, we will consider to extend this result to a class of nonlinear systems and establish the estimation of unknown gain parameter b_0. Then we will also consider how to use more system information to obtain the better system performance. Because the actuator failures and sensor failures are inevitable during the operation of the pneumatic muscle joint systems, the design of control scheme under unknown faults is also another important future work.

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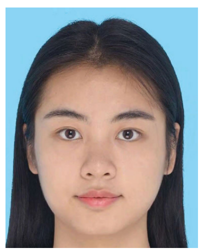

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