2019 IEEE 4th International Conference on Advanced
Robotics and Mechatronics (ICARM)

Nonlinear Disturbance Observer Based T-S Fuzzy Logic Control of Pneumatic Artificial Muscles

Cheng Chen, Jian Huang*, Dongrui Wu

***Abstract*— As a new type of actuator, pneumatic artificial muscle (PAM) possesses lots of superior characteristics, which make it extensively used in the robotics field, especially in rehabilitation engineering. But the complex dynamics such as time-varying parameters and hysteresis make it difficult to achieve high precision trajectory tracking control. In order to achieve accurate tracking performance and enhance the robustness of the controller, this paper proposes a nonlinear disturbance observer based T-S fuzzy logic controller (NDOTS). Based on the three-element model of PAM, T-S fuzzy modeling is utilized to decompose the nonlinear model into a series of linear models, which make it possible to use the linear system control theory in the controller design. The MATLAB LMI Toolbox is applied to get the feedback gains. A Lyapunov candidate is designed to analyze the stability of the system. The experimental results of attaching loads on the PAM validate the proposed NDOTS controller.**

***Index Terms*— Pneumatic Artificial Muscle(PAM), T-S Fuzzy Logic Control, Nonlinear Disturbance Observer(NDO), Trajectory Tracking Control.**

I. INTRODUCTION

Pneumatic artificial muscle (PAM) is a new type of actuator which is inspired by the natural tissue. Compared with traditional hydraulic actuators and electronic motors, PAM possesses lots of great virtues. Making use of the compressed air, PAM is an ecological actuator which is better for the environment. Besides, PAM is compliant for human use and has a really high power to weight ratio. No mechanical parts, low cost, and safety are also the advantages of PAM [1]. Therefore, PAMs are increasingly used in many robotic systems especially in rehabilitation engineering [2] where safety and compliance are usually attached great importance. However, in addition to many good advantages of being used as robotic actuators mentioned above, the hysteresis and the model coefficients varying with time make the traditional control strategies cannot achieve high precision accuracy. The extensive applications of PAMs are still facing challenges.

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Till now, various classical controllers have been adopted to achieve a high precision performance of PAMs [3], such as PID controller [4], SMC controller [5], neural network-based control [6] and fuzzy logic control [7]. The system stability of using the PID controller cannot be theoretically guaranteed, and the process of adjusting PID parameters is time-consuming. During the control process, the control law discontinuously crosses the sliding surface, so the SMC controller suffers from the chattering problem. Neural network-based controller can improve control performance by training the weights in neural networks, but the process of getting the optimal weights is also time-consuming.

As for fuzzy control, two main kinds of strategies are usually used. One is the Mamdani-type fuzzy control. The model-free Mamdani-type fuzzy controller is similar to the PID which can not guarantee the stability theoretically. Recently, interval type-2 (IT2) fuzzy sets are proposed. IT2 fuzzy sets which enhance the ability of the fuzzy system to deal with uncertainties effectively improve the performance of Mamdani-type controllers [8]. Besides, the selection of membership functions and the design of the fuzzy rules of the Mamdani-type fuzzy controller depends on the expert experiences, which makes the subjectivity of controller so strong that it's not reliable and rigorous theoretically, and lots of adjustments may be needed to modify the fuzzy rules. Compared with the Mamdani-type fuzzy controller, as a model-based control strategy, T-S fuzzy logic control proposed by Takagi in 1985 has sufficient theoretical basis [9] and its stability can be guaranteed through the direct method of Lyapunov. Hitherto, T-S fuzzy logic control has been extensively adopted in the robot control [10]. So T-S fuzzy logic control is a favorable choice in the high precision tracking control of PAMs.

However, the structure and parameters are completely fixed once the membership functions and fuzzy rules are chosen in T-S fuzzy logic control, which makes the control performance hard to be further improved, especially when there exited external disturbances and uncertainties of the dynamic model. Here we put forward a nonlinear disturbance observer [11] based T-S fuzzy logic controller (NDOTS) to overcome the perturbations including the modeling errors and the uncertainties of the model parameters to achieve high precision control. Utilizing the proposed NDOTS, the tracking performance of the single PAM system was effectively improved compared to the T-S fuzzy logic control (TS) without disturbance observer. Besides, the direct Lyapunov method guarantees the stability of the system. The LMI Toolbox of MATLAB 2013b is applied to simplify

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the process of getting the feedback gains of the control law. Finally, the experimental results validated the proposed NDOTS controller.

II. MODEL FORMULATION

The operating principle of a PAM is shown in Fig. 1. When the volume of the PAM increases because of the input of compressed air, the length of the PAM shortens, and thus generating pull to lift the target load. In practical applications, we can change the input pressure in the PAM to make it move as a reference trajectory or produce a force we need.

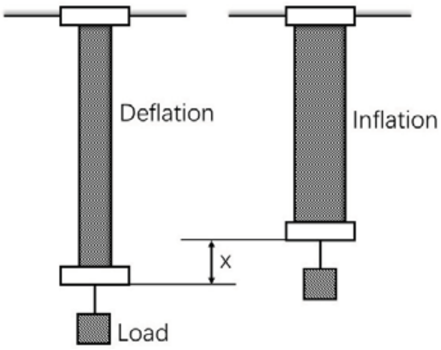

Fig. 1. The PAM operating diagram

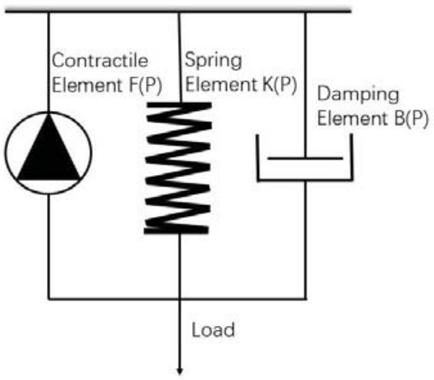

Fig. 2. The three-element model diagram

Due to the extensive applications of PAMs, since the PAM was invented, extensive research of the mathematical models of PAMs has been done so far. As shown in Fig. 2, the three-element model introduced by D.Reynolds [12] is adopted to describe the variety and complex dynamics of the PAM. The equations describing the dynamic characteristics of PAMs are as follow

$$m\ddot{y}+B\dot{y}+Ky=F-Mg \tag{1}$$

$$K=K_0+K_1p \tag{2}$$

$$B=B_{10}+B_{11}p \quad (inflation) \tag{3}$$

$$B=B_{20}+B_{21}p \quad (deflation) \tag{4}$$

$$F=F_0+F_1p \tag{5}$$

with M is the mass of loads. y is the displacement of the PMA. g is the acceleration of gravity. p is the inside air pressure of PAM. B denotes the damping coefficient and K indicates the spring coefficient. F is the pull exerted by the PAM. It's worth noting that damping coefficient B is related to the state of PAM, deflation or inflation, and there is a critical point p_0 where the equation of spring coefficient K will change.

$$K=K_{10}+K_{11}p \quad (p>p_0) \tag{6}$$

$$K=K_{20}+K_{21}p \quad (p<p_0) \tag{7}$$

III. CONTROL STRATEGIES

A. A SWITCH MODEL OF PAM WITH DISTURBANCES

In practical applications, the modeling errors and the parameter uncertainties inevitably deteriorate the control performance of PAMs. Here we introduce a disturbance term d to the dynamic model of the PAM. The equation describing the dynamics of PAMs with disturbances is

$$\begin{cases} \dot{x}_1(t)=x_2(t) \\ \dot{x}_2(t)=-\dfrac{K_0}{M}x_1-\dfrac{B_0}{M}x_2+(\dfrac{F_1}{M}-\dfrac{B_1x_2}{M} \\ \qquad -\dfrac{K_1x_1}{M})u+(\dfrac{F_0}{M}-g+d) \end{cases} \tag{8}$$

where $x_1=y$ and $x_2=\dot{y}$ and $u=p$ is the control input.

The state space representation of the dynamic model above is

$$\begin{bmatrix}\dot{x_1}\\ \dot{x_2}\end{bmatrix}=\begin{bmatrix}0 & 1\\ -\frac{K_0}{M} & -\frac{B_0}{M}\end{bmatrix}\begin{bmatrix}x_1\\ x_2\end{bmatrix}+\begin{bmatrix}0\\ f(x_1,x_2)\end{bmatrix}u+\begin{bmatrix}0\\ \eta\end{bmatrix} \tag{9}$$

$$\begin{aligned}\eta&=\frac{F_0}{M}-g+d\\ f(x_1,x_2)&=\frac{F_1}{M}-\frac{B_1x_2}{M}-\frac{K_1x_1}{M}\end{aligned} \tag{10}$$

The corresponding matrix form of (8)-(10) is

$$\dot{X}=AX+Bu+C \tag{11}$$

where

$$A=\begin{bmatrix}0 & 1\\ -\frac{K_0}{M} & -\frac{B_0}{M}\end{bmatrix},B=\begin{bmatrix}0\\ f(x_1,x_2)\end{bmatrix},C=\begin{bmatrix}0\\ \eta\end{bmatrix}$$

Because of the time-varying characteristics of PAM described in (3)-(4) and (6)-(7), here we propose a switch model of PAMs

$$\dot{X}=A_iX+B_iu+C \quad i=1,2,3,4. \tag{12}$$

$$A_1=\begin{bmatrix}0 & 1\\ -\frac{K_{10}}{M} & -\frac{B_{10}}{M}\end{bmatrix},B_1=\begin{bmatrix}0\\ -\frac{F_1}{M}-\frac{B_{11}x_2}{M}-\frac{K_{11}x_1}{M}\end{bmatrix}$$

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$$A_2 = \begin{bmatrix} 0 & 1 \\ -\frac{K_{20}}{M} & -\frac{B_{10}}{M} \end{bmatrix}, B_2 = \begin{bmatrix} 0 \\ -\frac{F_1}{M} - \frac{B_{11}x_2}{M} - \frac{K_{21}x_1}{M} \end{bmatrix}$$

$$A_3 = \begin{bmatrix} 0 & 1 \\ -\frac{K_{10}}{M} & -\frac{B_{20}}{M} \end{bmatrix}, B_3 = \begin{bmatrix} 0 \\ -\frac{F_1}{M} - \frac{B_{21}x_2}{M} - \frac{K_{11}x_1}{M} \end{bmatrix}$$

$$A_4 = \begin{bmatrix} 0 & 1 \\ -\frac{K_{20}}{M} & -\frac{B_{20}}{M} \end{bmatrix}, B_4 = \begin{bmatrix} 0 \\ -\frac{F_1}{M} - \frac{B_{21}x_2}{M} - \frac{K_{21}x_1}{M} \end{bmatrix}$$

where A_i and C are constant matrices. $f(x_1,x_2)$ in input matrix B_i is a nonlinear function of state variables x_1 and x_2. The PAM system switch between the four subsystems above according to the state of PAM (inflation or deflation, inner air pressure is big or small).

B. T-S FUZZY LOGIC CONTROLLER DESIGN

A typical T-S fuzzy system can be expressed as

$$\begin{aligned} &Rule\ r: \\ &\quad IF\ q_1(t)\ is\ I_{1r},\ q_2(t)\ is\ I_{2r} \cdots and\ q_h(t)\ is\ I_{hr} \\ &\quad THEN\ \dot{X} = A_r X + B_r u \quad r = 1,2\cdots\alpha \end{aligned} \tag{13}$$

where $q_h(t)$ is the premise variables. I_{hr} denotes fuzzy sets. α denotes the number of rules.

Three Gaussian membership functions are selected here. The T-S fuzzy model with three rules of the ith subsystem of the PAM is

$$\dot{X} = \sum_{\gamma=1}^{3} w_{i\gamma}(A_{i\gamma}X + B_{i\gamma}u + C) \tag{14}$$

where $w_{i\gamma}$ is the membership degree of the ith subsystem, and $\sum_{\gamma=1}^{3} w_{i\gamma} = 1$.

$$A_{i1} = A_{i2} = A_{i3}$$

$$B_{i1} = \begin{bmatrix} 0 \\ f_{min} \end{bmatrix}, B_{i2} = \begin{bmatrix} 0 \\ \frac{(f_{max}-f_{min})}{2} \end{bmatrix}, B_{i3} = \begin{bmatrix} 0 \\ f_{max} \end{bmatrix}$$

where f_{min} is the minimum value of $f(x_1,x_2)$ and f_{max} denotes the maximum value. Because the reference signal has been set in advance and the coefficients of the PAM model are known beforehand through the system identification, the normal range of $f(x_1,x_2)$ during the process of PAM operating can be estimated.

The reference signal $X_r = \begin{bmatrix} x_r \\ \dot{x}_r \end{bmatrix}$, and the error can be expressed as

$$E = X_r - X \tag{15}$$

The error system for each subsystem is constructed as

$$\dot{E} = \sum_{\gamma=1}^{3} w_{i\gamma}(A_{i\gamma}E + B_{i\gamma}\lambda_i) \tag{16}$$

where λ_i is the corresponding control input of the ith error system. And we rewrite the system (14) here

$$\dot{X} = \sum_{\gamma=1}^{3} w_{i\gamma}(A_{i\gamma}X + B_{i\gamma}u + C) \tag{17}$$

Substituting (15) and (17) into (16), we can get the following relationship between u and λ_i

$$\sum_{\gamma=1}^{3} w_{i\gamma}B_{i\gamma}u = \dot{X}_r - \sum_{\gamma=1}^{3} w_{i\gamma}A_{i\gamma}X_r - \sum_{\gamma=1}^{3} w_{i\gamma}B_{i\gamma}\lambda_i - C \tag{18}$$

The control input λ_i is

$$\lambda_i = -\sum_{k=1}^{3} w_{ik}H_{ik}E \tag{19}$$

where the feedback gains H_k are calculated through Parallel distributed compensation (PDC) method proposed in [9]. Finally, substituting (19) into (18) and letting $d = 0$ in (18), we can get the T-S fuzzy logic control signal u of PAM.

C. NONLINEAR DISTURBANCE OBSERVER BASED T-S FUZZY LOGIC CONTROL

To estimate the disturbances d, a nonlinear disturbance observer (NDO) $\hat{d}$ is introduced here. Rewrite the PAM system

$$\begin{bmatrix} \dot{x}_1 \\ \dot{x}_2 \end{bmatrix} = \begin{bmatrix} 0 & 1 \\ -\frac{K_0}{M} & -\frac{B_0}{M} \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \end{bmatrix} + \begin{bmatrix} 0 \\ f(x_1,x_2) \end{bmatrix} u + \begin{bmatrix} 0 \\ \eta \end{bmatrix} \tag{20}$$

$$\begin{aligned} \eta &= \frac{F_0}{M} - g + d \\ f(x_1,x_2) &= \frac{F_1}{M} - \frac{B_1x_2}{M} - \frac{K_1x_1}{M} \end{aligned} \tag{21}$$

In the form of vector, the PAM system can be represented as

$$\dot{X} = F(X) + \Phi_1(X)u + \Phi_2(X)d \tag{22}$$

with

$$F(X) = \begin{bmatrix} \dot{x}_2 \\ a(x_1,x_2) \end{bmatrix}, \Phi_1(X) = \begin{bmatrix} 0 \\ b(x_1,x_2) \end{bmatrix}, \Phi_2(X) = \begin{bmatrix} 0 \\ 1 \end{bmatrix}$$

$$\begin{cases} a(x_1,x_2) = -\frac{K_0x_1}{M} - \frac{B_0x_2}{M} + \frac{F_0}{M} - g & (23) \\ b(x_1,x_2) = \frac{F1}{M} - \frac{B_1x_2}{M} - \frac{K_1x_1}{M} & (24) \end{cases}$$

Based on the idea of adjusting the estimate of disturbance according to the difference between the estimate disturbance and actual disturbance, the disturbance observer was constructed as

$$\begin{cases} \hat{d} = z + p(X) & (25) \\ \dot{z} = L(-F(X) - \Phi_1(X)u - \Phi_2(X)\hat{d}) & (26) \\ L = \frac{\partial p(X)}{\partial X} & (27) \end{cases}$$

where $\hat{d}$ is the estimate of the actual disturbance term d, L is the constant disturbance observer matrix and $L = [c_1 \quad c_2]$. And $\tilde{d} = d - \hat{d}$ is the error between the estimate disturbance $\hat{d}$ and the actual disturbance d, which would be used in the later proof.

Finally, substituting this estimate disturbance $\hat{d}$ above into (19), we can obtain the disturbance observer based T-S fuzzy logic control signal.

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Theorem 1: The stability of the system can be guaranteed if we choose appropriate positive definite symmetry P, state feedback gains matrix H_{ik} and coefficients of nonlinear disturbance observer constant matrix $L = [c_1 \quad c_2]$ which satisfy the following inequalities:

$$\begin{cases} Q > 0 & (28) \\ QA_{i\gamma}^T + A_{i\gamma}Q + G_{ik}^T B_{i\gamma}^T + B_{i\gamma}G_{ik} < 0 & (29) \\ c_2 > 0 & (30) \end{cases}$$

where $P = Q^{-1}$ and $H_{ik} = -G_{ik}Q^{-1}$.

Proof: To guarantee the stability of (16), here we choose the following Lyapunov candidate:

$$V = E^T PE + \frac{1}{2}\tilde{d}^2 > 0 \tag{31}$$

The derivative of V can be expressed as

$$\begin{aligned} \dot{V} &= \dot{E}^T PE + E^T P\dot{E} + \tilde{d}\dot{\tilde{d}} \\ &= \sum_{\gamma=1}^{7}\sum_{k=1}^{7} w_{i\gamma}w_{\gamma k}(E^T((A_{i\gamma} - B_{i\gamma}H_{ik})^T P \\ &+ P(A_{i\gamma} - B_{i\gamma}H_{ik}))E) + \tilde{d}\dot{\tilde{d}} \end{aligned} \tag{32}$$

For the error term $\tilde{d}$ of disturbance observer, take the derivative of the $\hat{d}$ in (25) with the respect of time and substitute (26) and (27) into it, we can get

$$\dot{\hat{d}} = L(-F(X) - \Phi_1(X)u - \Phi_2(X)\hat{d}) + L\dot{X} \tag{33}$$

Then, substituting Eq.(22) into Eq.(33), we have

$$\dot{\hat{d}} = L\Phi_2(X)(d - \hat{d}) \tag{34}$$

Here we assume that the disturbance d change slowly with time, and thus, $\dot{d} = 0$. So we can obtain

$$\dot{\hat{d}} = -\dot{\tilde{d}} \tag{35}$$

Substitute (35) into (34), a differential equation of error $\tilde{d}$ can be obtained

$$\dot{\tilde{d}} + L\Phi_2(X)\tilde{d} = 0 \tag{36}$$

And substituting L and Φ_2, we have

$$\dot{\tilde{d}} + c_2\tilde{d} = 0 \tag{37}$$

Substituting (37) into (32), we get

$$\begin{aligned} \dot{V} &= \dot{E}^T PE + E^T P\dot{E} + \tilde{d}\dot{\tilde{d}} \\ &= \sum_{\gamma=1}^{7}\sum_{k=1}^{7} w_{i\gamma}w_{\gamma k}(E^T((A_{i\gamma} - B_{i\gamma}H_{ik})^T P \\ &+ P(A_{i\gamma} - B_{i\gamma}H_{ik}))E) - c_2\tilde{d}^2 \end{aligned} \tag{38}$$

The system is asymptotically stable if we can find a positive definite matrix P, an appropriate matrix H_{ik}, and a constant c_2 such that

$$\begin{cases} P > 0 & (39) \\ (A_{i\gamma} - B_{i\gamma}H_{ik})^T P + P(A_{i\gamma} - B_{i\gamma}H_{ik}) < 0 & (40) \\ c_2 > 0 & (41) \end{cases}$$

However, the inequalities (40) are not the standard LMI forms which are able to be directly solved by the LMI Toolbox. Here we define

$$Q = P^{-1} \tag{42}$$

Substituting (42) into (40), we get

$$QA_{i\gamma}^T - QH_{ik}^T B_{i\gamma}^T + A_{i\gamma}Q - B_{i\gamma}H_{ik}Q < 0 \tag{43}$$

Let:

$$-H_{ik}Q = G_{ik} \tag{44}$$

Then (29) can be transformed into a standard LMI form

$$QA_{i\gamma}^T + A_{i\gamma}Q + G_{ik}^T B_{i\gamma}^T + B_{i\gamma}G_{ik} < 0 \tag{45}$$

In summary, we can obtain the following inequalities for the system stability

$$\begin{cases} Q > 0 & (46) \\ QA_{i\gamma}^T + A_{i\gamma}Q + G_{ik}^T B_{i\gamma}^T + B_{i\gamma}G_{ik} < 0 & (47) \\ P = Q^{-1} & (48) \\ H_{ik} = -G_{ik}Q^{-1} & (49) \\ c_2 > 0 & (50) \end{cases}$$

Adopting the LMI Toolbox of Matlab, the inequalities above can be easily solved. ■

IV. EXPERIMENTAL RESULTS

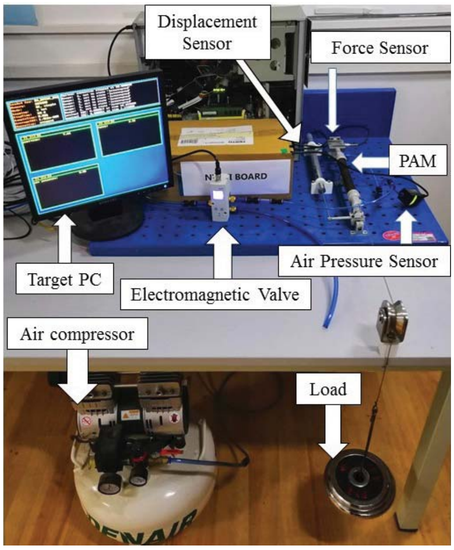

Fig. 3. The Experiment Platform

An experiment is implemented in the real-world PAM platform shown in Fig. 3. The sampling time is $0.0001\,s$. Based on the previous work of [9], the coefficients of PAM used in this experiment are identified in the same way. Table I lists the model coefficients of PAM and the critical point $P_0 = 325420P_a$. Here we choose the following reference trajectory

$$X_r = 0.0125 - 0.0125cos(0.5\pi t) \tag{51}$$

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TABLE I
THE COEFFICIENTS OF THE PAM

Parameter	Value(Unit)	Parameter	Value(Unit)
F_0	-202.32(N)	F_1	0.007(N/Pa)
K_{10}	17845(N/m)	K_{11}	0.011(N/m Pa)
K_{20}	77548(N/m)	K_{21}	-0.206(N/m Pa)
B_{10}	1546(N s/m)	B_{11}	0.067(N s/m Pa)
B_{20}	15424(N s/m)	B_{21}	0.0040(N s/m Pa)

Substituting the model coefficients into (10)-(11), using LMI Toolbox of MATLAB, we can get the feedback gains H_{ik} of four subsystems shown in Table II and III. The constant nonlinear disturbance observer matrix is: $L = [-5000\ 0.003]$. And the positive symmetric matrix of each subsystem are

$$P_1 = \begin{bmatrix} 4981.94 & 431.57 \\ 431.57 & 37.67 \end{bmatrix}, P_2 = \begin{bmatrix} 638.73 & 12.73 \\ 12.73 & 0.26 \end{bmatrix}$$

$$P_3 = \begin{bmatrix} 1672.39 & 1445.42 \\ 1445.42 & 1249.42 \end{bmatrix}, P_4 = \begin{bmatrix} 10672.18 & 2122.62 \\ 2122.62 & 422.32 \end{bmatrix}$$

TABLE II
STATE FEEDBACK GAINS H_{ik}, $i = 1, 2$

H_{ik}	i=1	2
k=1	[-7894.08 -683.86]	[-5823.10 -116.08]
2	[-7894.08 -683.86]	[-5823.10 -116.08]
3	[-7894.08 -683.86]	[-5823.10 -116.08]

TABLE III
STATE FEEDBACK GAINS H_{ik}, $i = 3, 4$

H_{ik}	i=3	4
k=1	[-79712.66 -68896.80]	[-94369.74 -18769.63]
2	[-79712.66 -68896.80]	[-94369.74 -18769.63]
3	[-79712.66 -68896.800]	[-94369.74 -18769.63]

To evaluate the control performance of the proposed nonlinear disturbance observer based T-S fuzzy logic control (NDOTS), in the experiment, we compared the trajectory tracking results of the traditional PID controller, T-S fuzzy logic controller (TS) without disturbance observer and NDOTS. Besides, to further test the robustness of control strategies, 2.5kg loads were attached to the PAM.

Fig. 4 shows the trajectory tracking performances of PAM without load and the corresponding errors are presented in fig. 5. From fig. 5, we can easily find that in the case of PAM without load, the control performances of PID and nonlinear disturbance observer based T-S fuzzy logic control (NDOTS) are similar. The maximum absolute error of PID is 0.83mm, and that of NDOTS is 0.74mm. The maximum absolute error of T-S fuzzy logic control (TS) is 1.18mm, which is larger than that of NDOTS and PID. Experimental results turn out that the proposed NDOTS strategy can achieve the highest tracking precision.

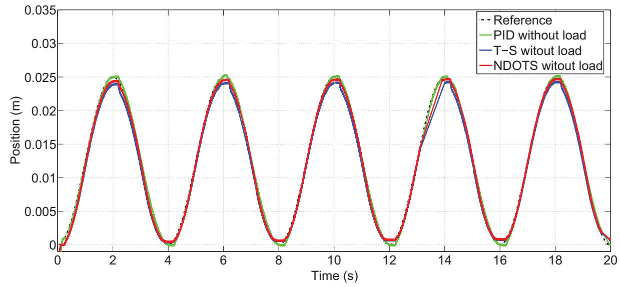

Fig. 4. Trajectory tracking results of PAM without load.

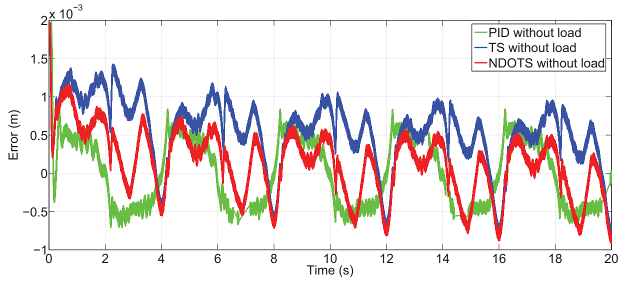

Fig. 5. Tracking errors of PAM without load.

As a model-free controller, no model coefficients of PAM need to be concerned in the PID controller, so using trial-and-error, the tracking performance of PID can be adjusted to a high precision level. The parameters used in the PID controller are $P = 1.0e+7$, $I = 2.1e+8$ and $D = 1.0e+3$. For TS and NDOTS, in the practical experiments, the three elements model of PAM and its coefficients are not completely accurate, so T-S fuzzy logic can not characterize the dynamics of PAM accurately. Therefore, the control performance of TS would be influenced inevitably. In this paper, NDOTS introduces the nonlinear disturbance observer (NDO) into T-S fuzzy logic control. The model inaccuracy and uncertainty are largely compensated by the NDO, and thus, the performance of NDOTS is the best.

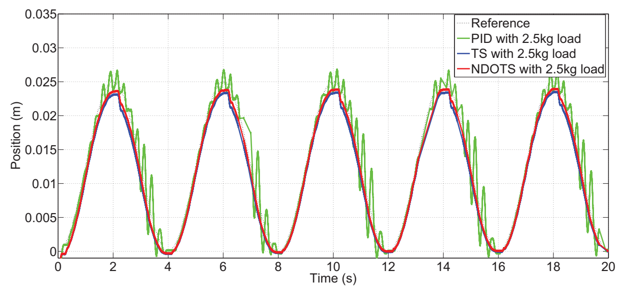

Fig. 6. Trajectory tracking results of PAM with a 2.5kg load.

Fig. 6 shows the control performance of the three control strategies with 2.5kg loads. Fig. 7 is the corresponding tracking errors. We can find that the control performance

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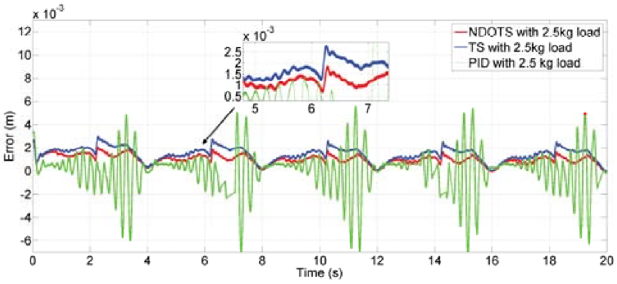

Fig. 7. Tracking errors of PAM with a 2.5kg load.

of PID deteriorates a lot when attaching loads on the PAM. The external disturbance can largely influence the PID controller. The maximum absolute error of PID is up to 7.4*mm*. However, the control performance of TS and NDOTS can still keep at a high level of precision, and the NDOTS has the smallest maximum absolute errors, 1.88*mm* with 2.5kg loads.

V. CONCLUSIONS

This paper proposes a novel nonlinear disturbance observer based T-S fuzzy logic control strategy (NDOTS) for the single PAM system. To eliminate the effect of the time variant dynamics of PAM, we introduce a switch model first. The nonlinear PAM model is linearized by means of T-S fuzzy modeling so that we can use the parallel distributed compensation (PDC) method, a linear control theory based approach get the control input. LMI Toolbox is used to quickly solve the control gains. To compensate for the modeling errors and its coefficients uncertainties, a nonlinear disturbance observer is introduced to the T-S fuzzy logic controller. Besides, a Lyapunov candidate is designed and we analyze the system stability. Finally, the experimental results validate the high control precision and better robustness of the proposed NDOTS.

ACKNOWLEDGMENT

This work was supported in part by the National Natural Science Foundation of China under Grant 61873321, 61473130 and the research fund of PLA of China (B-WS17J024).

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