ADAPTIVE ROBUST TRACKING CONTROL OF PRESSURE TRAJECTORY BASED ON KALMAN FILTER *

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Abstract: For the adaptive robust control (ARC) strategy based on backstepping design, tracking control of both force trajectory and position trajectory need the high-precision pressure control in pneumatic systems. In this paper, an adaptive robust pressure controller is designed to enhance the tracking accuracy of pressure trajectory in the chamber when the pneumatic cylinder is moving. Off-line fitting of the effective throttling area and on-line parameter estimation of flow coefficient are used to improve the model compensation in the adaptive term, and robust feedback and Kalman filter are used to achieve strong robustness. Experimental results show that the proposed adaptive robust pressure controller not only achieves good tracking of pressure trajectory even when the pneumatic cylinder is moving, but also obtains very smooth control input which indicates the effectiveness of model compensation.

Key words: Pneumatic servo control Adaptive robust control Kalman filtering Effective throttling area

0 INTRODUCTION

The compressibility of air and the inherent nonlinearity of pneumatic systems continue to make pneumatic servo system a research focus [1]. The high-precision posture control of parallel manipulator driven by pneumatic muscles is realized through applying adaptive robust control strategy into it [2]. Therefore, it is an attempt that applying this strategy to the pneumatic cylinder with large friction force for achieving the high-precision trajectory tracking of force and position. For the adaptive robust control strategy based on backstepping design, tracking control of both force trajectory and position trajectory need the high-precision pressure control in pneumatic systems [3].

For the constant pressure control or step response of pressure control in pneumatic systems, only PID algorithm controlling a proportional valve is needed to achieve better steady-state error. However, for the tracking control of sinusoidal pressure trajectory and even arbitrary pressure trajectory, the PID algorithm would bring about large tracking error and severe control input chattering, so this algorithm could not realize the high-precision trajectory tracking of force and position. Therefore, it is necessary to utilize the adaptive model compensation for improving the tracking accuracy of pressure trajectory and use robust feedback for guaranteeing the strong robustness of pneumatic system. The key to model compensation lies in realizing the nonlinear compensation of mass flow rate and pressure dynamics. Richer and Hurmuzlu proposed the accurate models of pressure dynamics in pneumatic cylinder, time delay and attenuation in pneumatic lines, valve dynamics, flow nonlinearities through the valve orifice, piston friction force, and identified unknown parameters of the above models through using specially designed experiments [4]. Moreover, a nonlinear sliding mode controller is designed on the basis of the above models to achieve the high-precision tracking control of sinusoidal force trajectory. However, it is very difficult to obtain so much a number of geometric and functional characteristics or parameters of pneumatic cylinder and proportional directional valve. Thereby, many researchers use off-line identification for controlling the force or position on the basis of obtaining common geometric and functional characteristics or parameters [1,5]. In this paper, the off-line curve fitting and on-line identification for the models are combined to achieve better adaptive robust tracking control of pressure trajectory.

Recently, the tendency of applying pneumatic control to bionic robot is more and more obvious [6,7]. For the future, pneumatic servo control would not be limited to tracking the deterministic trajectory, and would extend to tracking the arbitrary trajectory. In this way, the statistical property of noises may be unknown and time-varying. Therefore, Kalman filter would be used to attenuate the influences of process noise and measurement noise and improve the filtering accuracy. Moreover, the first-order difference of pressure could be obtained by Kalman filter, which would be convenient for designing an adaptive robust motion controller in the future.

1 SYSTEM DYNAMICS

1.1 Schematic diagram of pneumatic system

The schematic diagram of pneumatic system is shown in Fig. 1. Two proportional directional valves(MPYE-5- 1/8–HF-010B by FESTO) separately control two chambers of rodless pneumatic cylinder(DGPIL-25-500-6K-KF-AU by FESTO) , three pressure transducers(SDET-22T-D10-G14-I-M12 by FESTO) are used to measure the pressures of chamber A, chamber B and supply pressure respectively, and a position transducer (RPS0500MD601V810050 by MTS) is used to measure the position and velocity of rodless pneumatic cylinder. Since two valves separately control the two chambers of cylinder, there exist two control degrees of freedom in the system, thus two different trajectories can be controlled. For example, motion trajectory and pressure trajectory, motion trajectory and energy trajectory, or motion trajectory and stiffness trajectory. Moreover, the system would be controlled completely since there is no zero

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dynamics in it. In this paper, chamber A is used to track a motion trajectory by open-loop control and chamber B track a pressure trajectory by closed-loop control.

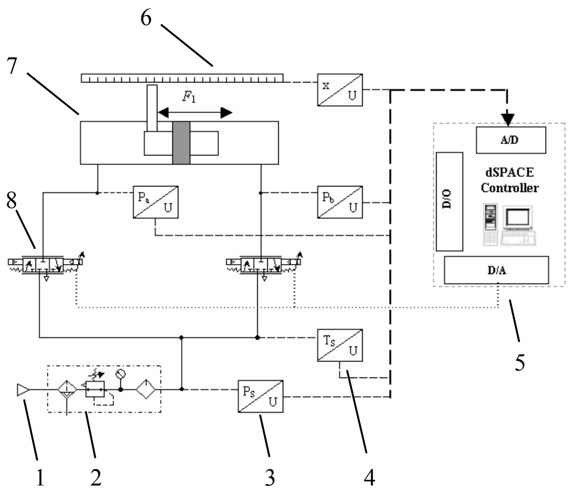

Fig.1 Schematic diagram of pneumatic system

1.air supply 2.air treatment unit 3.pressure transducer 4.temperature transducer 5.dSPACE controller 6.position transducer 7.rodless pneumatic cylinder 8.proportional directional valve

1.2 Pressure dynamics in pneumatic cylinder

Theoretical expression for pressure dynamics in chamber can be obtained by equation of state for ideal gas, continuity equation for steady one-dimensional flow, and first law of thermodynamics. However, the above theoretical expression needs the temperature in chamber for the discharging process. In fact, it have been found by researchers that the experimental values of the temperature were close to the adiabatic curve only for the charging process and they were close to the isothermal assumption for the discharging process [4]. Therefore, Richer and Hurmuzlu presented an integrated expression of pressure dynamics(chamber B) shown in Eq.(1). Therein, $\alpha_{in}=1.4$, $\alpha_{out}=1.0, \alpha=1.2$。

$$\dot{p}_b=\frac{RT_s}{V_b}\left(\alpha_{in}q_{in}-\alpha_{out}q_{out}\right)+\alpha\frac{p_bA_b}{V_b}\dot{x}+d_p(t) \tag{1}$$

where R is the perfect gas constant, T_s is the upstream temperature of proportional directional valve, V_b is the volume of air in chamber B, p_b is the pressure of air in chamber B, $d_p(t)$ is the lumped disturbance of whole system.

1.3 Mass flow rate of proportional directional valve

When the proportional directional valve is in the dead zone of neutral position, the leakage mass flow rate is biggish. Moreover, the valve would work in the dead zone when the pressure control is steady at certain constant value. Therefore, it is necessary to model accurately the mass flow rate in the dead zone in order to reduce control input chattering and enhance the accuracy of pressure control. When the valve is at neutral position, the leakage mass flow rate is described by annular flow model that is proportional to differential pressure. When the valve is open, the mass flow rate through orifice is regarded as the nozzle flow model. To facilitate the design of nonlinear controller, the leakage mass flow rate is also described by the nozzle flow model and then this implies the curve fitting in the sense of leakage throttling area. Through measuring the mass flow rate under different control voltages, the relation between control voltage and effective throttling area could be obtained as shown in Fig.2.

The critical pressure ratio P_{cr} in theoretical formula is not equal to the critical pressure ratio b in flow formula of

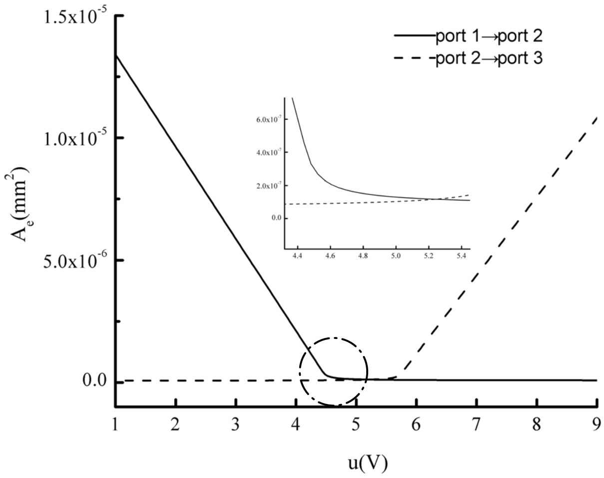

Fig.2 Relation between control voltage and effective throttling area

ISO6358. For guaranteeing the effective model compensation in the controller, the experimental value of critical pressure ratio b would be regarded as the transition point between sonic flow and subsonic flow. At the same time, for keeping the segment function continuous, the following equation of mass flow rate will be used (charging process) [9].

$$q=A_eC_qC_m\frac{p_s}{\sqrt{T_s}} \tag{2}$$

where A_e is the effective throttling area of valve, C_q is flow coefficient, p_s is the supply pressure of valve, and flow parameter C_m is expressed as

$$C_m=\begin{cases}\sqrt{\dfrac{\gamma}{R}\left(\dfrac{2}{\gamma+1}\right)^{\frac{\gamma+1}{\gamma-1}}} & 0<\dfrac{p_b}{p_s}\le b\\ C_t\sqrt{\dfrac{2\gamma}{R(\gamma-1)}}\sqrt{1-\left(\dfrac{\dfrac{p_b}{p_s}-b}{1-b}\right)^2} & b<\dfrac{p_b}{p_s}\le\lambda\\ \dfrac{\left(\dfrac{p_b}{p_s}\right)-1}{\lambda-1}C_t\sqrt{\dfrac{2\gamma}{R(\gamma-1)}}\sqrt{1-\left(\dfrac{\lambda-b}{1-b}\right)^2} & \lambda<\dfrac{p_b}{p_s}\le 1\end{cases} \tag{3}$$

in which λ is the minimal pressure ratio to have a laminar flow, $C_t=0.2588$ is a correction factor between theoretical value and experimental value of critical pressure ratio.

Flow coefficient C_q is used to include extra losses due to local friction and loss of kinetic energy, it is related to the ratio between downstream pressure and upstream pressure, and assumed to be polynomial function of the pressure ratio according to Perry's law [9]. Being enlightened by his method, the flow coefficient is expressed as the polynomial function of pressure ratio to reflect that the flow coefficient varies according to the pressure. Moreover, coefficients of polynomial function will be identified on-line for reducing model errors in the adaptive robust controller.

$$C_q=a_0+a_1\left(\frac{p_b}{p_s}\right)+a_2\left(\frac{p_b}{p_s}\right)^2 \tag{4}$$

where a_0,a_1,a_2 are all unknown parameters and will be identified on-line.

2 DESIGN OF ADAPTIVE ROBUST PRESSURE CONTROLLER

There still exist model errors in the system from pressure dynamics in pneumatic cylinder, mass flow rate of valve and temperature in chamber. Thus, model errors will be lumped into the disturbance $d_p(t)$ in Eq.(1) and $d_p(t)=d_{p0}+\tilde{d}_p(t)$. Therein, d_{p0} is the slow time-varying part of lumped disturbance in models (also nominal value of lumped disturbance), and $\tilde{d}_p(t)$ is the fast time-varying part of lumped disturbance. Then, Eq.(1) could be rewritten as Eq.(5). As the length of paper is limited, the adaptive robust pressure controller for charging process is designed in chamber B while the controller for discharging process is similar to this procedure.

$$\dot{p}_b=\frac{RT_s}{V_b}\left(\alpha_{in}q_{in}-\alpha_{out}q_{out}\right)+\alpha\frac{p_bA_b}{V_b}\dot{x}+d_{p0}+\tilde{d}_p(t) \tag{5}$$

2.1 Adaptive robust pressure controller

As can shown in Eq. (2) and Eq. (5), unknown parameters C_q, d_{p0} in system models will be updated on-line through adaptive parameter estimation to improve control accuracy. Meanwhile, a discontinuous projection mapping is utilized to guarantee that the parameter estimates and their derivatives remain in the known bounded region all the time [10]. Then the adaptive robust controller based on backstepping design is synthesized as follows.

(1) Step 1

Denote pressure error as $e_p=p_b-p_{bd}$ in which p_{bd} is desired pressure trajectory. From Eq. (5), the dynamics of e_p is

$$\begin{aligned}\dot{e}_p&=\dot{p}_b-\dot{p}_{bd}\\&=\frac{RT_s}{V_b}\left(\alpha_{in}q_{in}-\alpha_{out}q_{out}\right)+\alpha\frac{p_bA_b}{V_b}\dot{x}-\dot{p}_{bd}+d_{p0}+\tilde{d}_p(t)\end{aligned} \tag{6}$$

Define virtual mass flow rate as $q_m=\alpha_{in}q_{in}-\alpha_{out}q_{out}$, then Eq.(6) can be rewritten as

$$\dot{e}_p=\frac{RT_s}{V_b}q_m+\alpha\frac{p_bA_b}{V_b}\dot{x}-\dot{p}_{bd}+d_{p0}+\tilde{d}_p(t) \tag{7}$$

The desired virtual mass flow rate q_{md} is

$$q_{md}=q_{mda}+q_{mds} \tag{8}$$

$$q_{mda}=-\alpha\frac{p_bA_b}{RT_s}\dot{x}-\frac{V_b}{RT_s}\hat{d}_{p0}+\frac{V_b}{RT_s}\dot{p}_{bd} \tag{9}$$

where q_{mda} is the model compensation term in ARC and q_{mds} is the robust feedback term in ARC, which consists of the following linear part and nonlinear part.

$$q_{mds}=q_{mds1}+q_{mds2} \tag{10}$$

$$q_{mds1}=-k_pe_p\frac{V_b}{RT_s} \tag{11}$$

$$q_{mds2}=-k_{s1}\left(\frac{e_p}{\eta}\right)\frac{V_b}{RT_s} \tag{12}$$

where k_p, k_{s1}, η are all positive parameters.

Let $\tilde{d}_{p0}=\hat{d}_{p0}-d_{p0}$ and define the positive semi-definite Lyapunov function as $V_p=\frac{1}{2}e_p^{\ 2}$, one obtains

$$\dot{V}_p=-k_pe_p^{\ 2}+e_p\left(\frac{RT_s}{V_b}q_{mds2}-\tilde{d}_{p0}+\tilde{d}_p(t)\right) \tag{13}$$

q_{mds2} is synthesized to dominate the uncompensated model uncertainties coming from both parametric uncertainties and uncertain nonlinearities, which is chosen to satisfy the following conditions.

$$\begin{cases}e_p\left(\dfrac{RT_s}{V_b}q_{mds2}-\tilde{d}_{p0}+\tilde{d}_p(t)\right)\le\varepsilon_p\\ e_p\dfrac{RT_s}{V_b}q_{mds2}\le 0\end{cases} \tag{14}$$

where ε_p is a positive design parameter that may be arbitrarily small.

Substituting Eq.(14) into Eq.(13), one obtains the following equation for guaranteeing Lyapunov stability.

$$\dot{V}_p=-k_pe_p^{\ 2}+e_p\left(\frac{RT_s}{V_b}q_{mds2}-\tilde{d}_{p0}+\tilde{d}_p(t)\right)\le -k_pe_p^{\ 2}+\varepsilon_p \tag{15}$$

$\hat{d}_{p0}$ is updated by an adaptation law as follows.

$$\dot{\hat{d}}_{p0}=\mathrm{Proj}_{\hat{d}_{p0}}\left(\Gamma_1\sigma_1\right) \tag{16}$$

with the adaptation function given by

$$\sigma_1=\varphi_1e_p \tag{17}$$

Define augmented Lyapunov function as $V_{pa}=V_p+\frac{1}{2}\tilde{d}_{p0}^{\ 2}$, the time derivative of V_{pa} is

$$\dot{V}_{pa}=\dot{V}_p+\tilde{d}_{p0}\dot{\tilde{d}}_{p0}=-k_pe_p^{\ 2}+e_p\frac{RT_s}{V_b}q_{mds2}+\tilde{d}_{p0}\left(\dot{\tilde{d}}_{p0}-e_p\right) \tag{18}$$

Due to $\dot{\tilde{d}}_{p0}=\dot{\hat{d}}_{p0}$, the regressor is $\varphi_1=1$.

(2) Step 2

C_q is also updated by on-line parameter estimation according to the pressure dynamics of system Eq. (5) for further reducing the influences of model errors. To bypass the problem that numerical differentiation of pressure feedback signal would result in severe noise if it were adopted by parameter estimation, a stable filter with a relative degree larger than or equal to 1 would be employed in pressure dynamics and $\tilde{d}_p(t)=0$ would be assumed [11], and then a standard linear regression model for parameter estimation could be obtained.

$$y=\dot{p}_{bf}=\varphi_{2f}^{\ T}\beta \tag{19}$$

where $\dot{p}_{bf}$ is the filtered output of $\dot{p}_b$, φ_{2f} is the corresponding regressor of β, and $\beta=[a_0,a_1,a_2]^T$.

The least squares type estimation algorithm is used to estimate unknown parameter β [12], and a discontinuous projection mapping is used to keep parameter estimates bounded. β is updated by an adaptation law as follows.

$$\dot{\hat{\beta}}=\mathrm{Proj}_{\hat{\beta}}\left(\Gamma_2\sigma_2\right) \tag{20}$$

with the adaptation function given by

$$\sigma_2=-\frac{1}{1+v\cdot tr\left\{\varphi_{2f}^{\ T}\Gamma_2\varphi_{2f}\right\}}\varphi_{2f}\Gamma_2 \tag{21}$$

and the adaptation rate matrix given by

$$\dot{\Gamma}_2=\alpha_2\Gamma_2-\frac{1}{1+v\cdot tr\left\{\varphi_{2f}^{\ T}\varphi_{2f}\right\}}\Gamma_2\varphi_{2f}\varphi_{2f}^{\ T}\Gamma_2 \tag{22}$$

where $\alpha_2\ge 0$ is the forgetting factor, $v\ge 0$

(3) Step 3

After q_{md} and C_q is calculated, the control input of

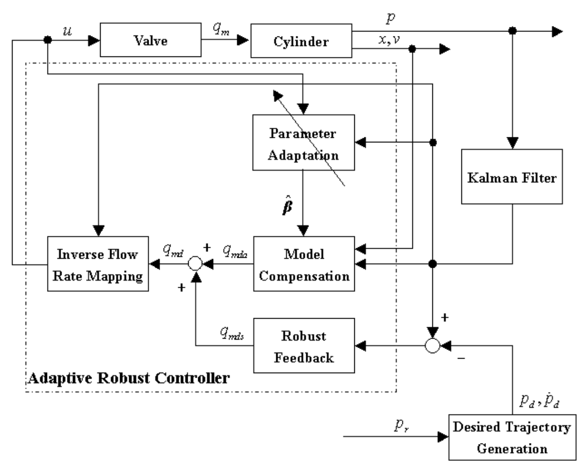

Fig.3 Principle of pressure tracking control

proportional directional valve could be obtained according to equation of mass flow rate (Eq.(2)) and relation between control voltage and effective throttling area(Fig. 2).

2.2 Principle of pressure tracking control

Putting all the development together, the adaptive robust pressure controller for the pneumatic system based on separate control of motion trajectory and pressure trajectory is schematically represented in Fig.3.

3 KALMAN FILTER

For reducing influences of process noise and measurement noise on the measured signals, the following Kalman filter would be adopted to get the pressures of air supply and chamber B in order to improve the filtering accuracy of measured signals.

Define the state vector of system as $x=[p_b,\dot{p}_b]^T$ assume the sampling period T_s very small, and then the state equation and observation equation of the system could be expressed as follows respectively [8].

$$x(k)=Ax(k-1)+Bw(k-1) \tag{23}$$

$$y(k)=Cx(k)+v(k) \tag{24}$$

where A is the state transition matrix, B is the input matrix of process noise, C is the observation matrix, w and v are process noise and measurement noise respectively with the assumption that they are all separate zero-mean guassian white noise.

The Kalman filter is designed as

$$\begin{cases} \hat{x}(k,k-1)=A\hat{x}(k-1) \\ \hat{x}(k)=\hat{x}(k,k-1)+K(k)\left[y(k)-C\hat{x}(k,k-1)\right] \\ P(k,k-1)=AP(k-1)A^T+BQB^T \\ K(k)=P(k,k-1)C^T\left[CP(k,k-1)C^T+R\right]^{-1} \\ P(k)=\left[I-K(k)C\right]^{-1}P(k,k-1) \end{cases} \tag{25}$$

where $P(k)$ is the covariance matrix of observation errors, $K(k)$ is the Kalman gain matrix, Q is the covariance of process noise, and R is the covariance of measurement noise.

When the filtering time is enough, $\lim_{k\to\infty}P(k)=P$, $\lim_{k\to\infty}K(k)=K=\left[\alpha,\beta\right]^T$, and parameters of filter α,β tend to be stable.

4 EXPERIMENTAL RESULTS

The effectiveness of the proposed controller has been demonstrated by a number of experiments under the supply pressure of 0.45MPa. It must be noted that the supply pressure would decrease a little during the tracking control of pressure trajectory with the drop of 8.9% when tracking a smooth step trajectory and the drop of 7.4% when tracking a sinusoidal trajectory.

4.1 Tracking of step pressure trajectory through desired trajectory generation

For tracking a step pressure trajectory through desired trajectory generation, response comparison between ARC and PID is shown in Fig.5. It must be noted that open-loop tracking control of motion trajectory is conducted from 4s to 7s in order that performance index under the control of two controllers could be compared when the pneumatic cylinder is moving (Fig.4). As can be seen from Fig.6, maximum tracking error of ARC is 4.5kPa, average tracking error is 1.1kPa and steady-sate error is 1.0kPa, however, maximum tracking error of PID is 9.3kPa, average tracking error is 4.0kPa and steady-sate error is 2.3kPa. Therefore, it can be concluded that tracking errors of ARC are much smaller than those of PID and steady-state error of ARC is close to the measurement accuracy of pressure transducer, and especially that ARC could achieve high-precision pressure tracking when the pneumatic cylinder is moving.

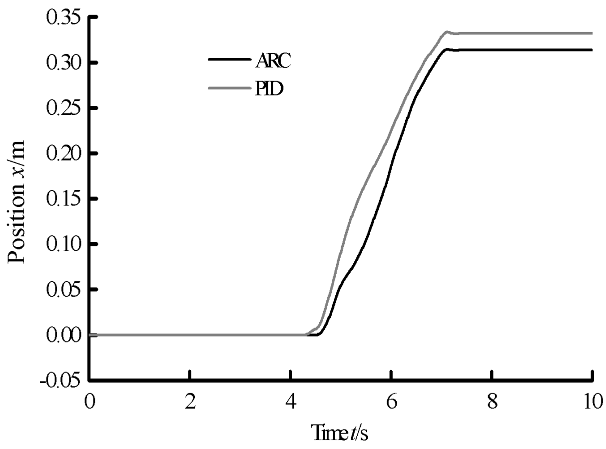

Fig.4 Open-loop motion tracking control of pneumatic cylinder

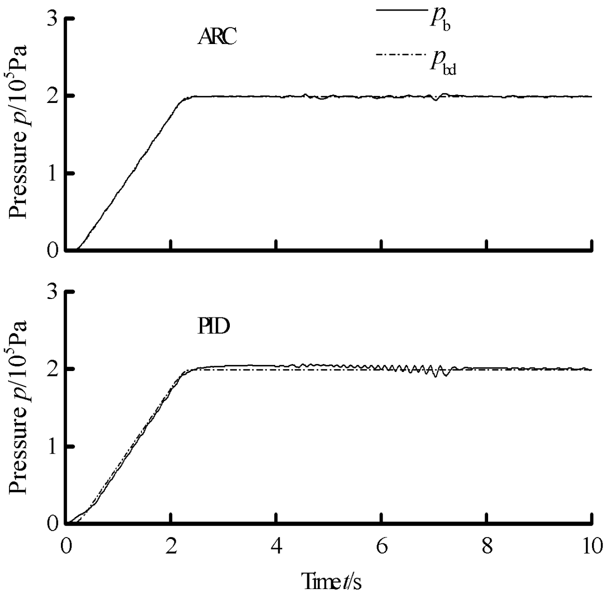

Fig.5 Tracking responses of step pressure trajectory

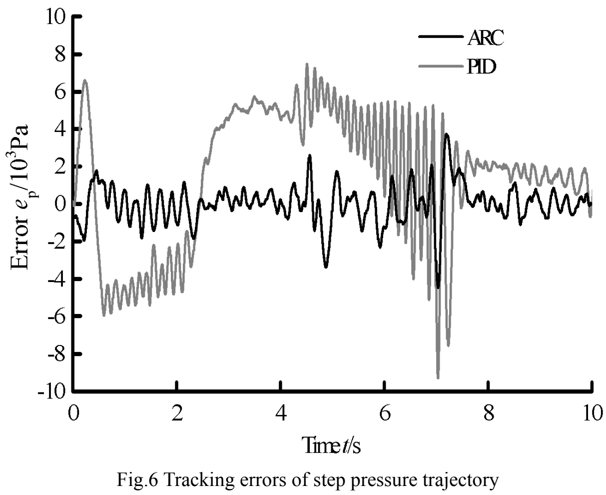

Fig.6 Tracking errors of step pressure trajectory

4.2 Tracking of sinusoidal pressure trajectory

For tracking a sinusoidal pressure trajectory, response comparison between ARC and PID is shown in Fig.7. It is well known from Fig.8 that maximum tracking error of ARC is 3kPa but that of PID reaches 11kPa and that average tracking error of ARC is only 1.4kPa while that of PID is 7.8kPa. Moreover, as can be seen from the control input of two controllers in Fig.9, the control input of ARC is very smooth while there exists control chattering in PID. Therefore, tracking errors of ARC are much smaller than those of PID with the merit of smooth control input.

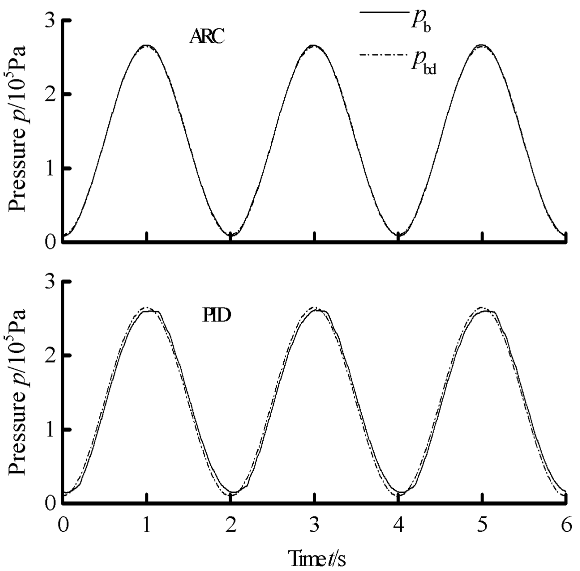

Fig.7 Tracking responses of sinusoidal pressure trajectory

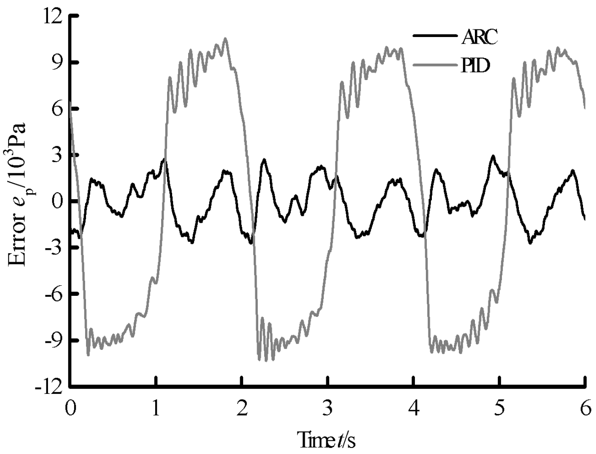

Fig.8 Tracking errors of sinusoidal pressure trajectory

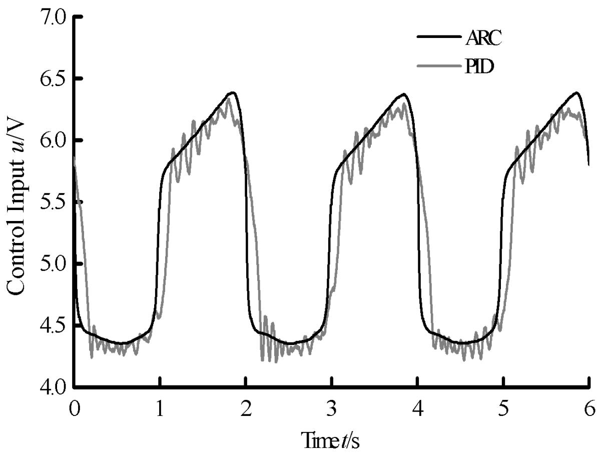

Fig.9 Control inputs of tracking a sinusoidal pressure trajectory

5 CONCLUSIONS

An adaptive robust pressure controller is proposed to enhance the tracking accuracy of pressure trajectory in the chamber when the pneumatic cylinder is moving. Off-line fitting of the effective throttling area and on-line parameter estimation of flow coefficient are used to improve the model compensation in the adaptive term, and robust feedback and Kalman filter are used to achieve strong robustness.

For tracking a step pressure trajectory with the movement of pneumatic cylinder, maximum tracking error of ARC is 4.5kPa and average tracking error is 1.1kPa, and steady-state error of ARC is close to the measurement accuracy of pressure transducer. For tracking a sinusoidal pressure trajectory, maximum tracking error of ARC is 3kPa and average tracking error is 1.4kPa. Therefore, tracking errors of ARC are much smaller than those of PID with the merit of very smooth control input, which verifies the effectiveness of the adaptive robust pressure controller.

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