An Intelligent Adaptive Robust Controller Based on Neural Network for a Pneumatic System

Ye Chen¹, Guoliang Tao¹,², Fangan Meng²
¹State Key Laboratory of Fluid Power & Mechatronic Systems, Zhejiang University, Hangzhou, Zhejiang, China
²DJI-Innovations, Shanghai, China
³gltao@zju.edu.cn

Abstract. Pneumatic actuator systems are widely applied in industrial automation. This paper proposes an intelligent adaptive robust controller (ARC) based on neural network (NN) to improve the applicability in a pneumatic servo system that consists of a pneumatic cylinder which is controlled by a proportional directional control valve. In this design, adaptive robust controller is provided with suitable control parameters automatically by a real-time neural network depending on feedback errors. So the ARC the tuning process that is time consuming and restricts the application of pneumatic systems is avoided. The experimental results show all the control parameters of ARC are converged and good control performance is achieved.

1. Introduction

Pneumatic actuator systems are of interest for industrial applications as they have the main advantages of high power to weight ratio, cleanliness, simplicity of operation, and low cost [1]. But due to dynamic highly nonlinear, severe parametric uncertainties and uncertain nonlinearities of pneumatic systems, it is difficult to control the pneumatic systems [2-3].

A large body of research is aimed for improving performance of servo pneumatic systems. For example, conventional linear controllers is developed including PID gain scheduling techniques [4] and nonlinear state feedback techniques [5-6]. As an example of nonlinear control, sliding mode control for pneumatic system is proposed by Ning and Bone [7]. As a more recent example, Deyuan Meng [8] applied ARC to the servo pneumatic system and experiment results showed good tracking performance. ARC is effective as it reduces the extent of parametric uncertainties through utilizing on-line recursive least squares estimation, and attenuates the effects of parameter estimation errors, disturbances and unmodeled dynamics by employing sliding mode control method [9]. However, the tuning process of ARC by try-and-error for pneumatic systems restricts the application of the control scheme.

Neural network has been highly applied for many different areas [10-12]. As the tuning problem, Gi et al. designed feedback linearization controller with a neural network which is training off-line [13]. Results showed tracking performance with NN much better than non-NN-compensated controller. Behrad [14] reported success with a novel NNC with PID for pneumatic gantry robot. Kothapalli and Hassan [15] used an off-line NN to adjust the gains of a PI position controller of a pneumatic system. Simulation shows NN could improve the performance.

This paper sets out to document a novel neural network based intelligent adaptive robust controller to improve the applicability in servo pneumatic actuator. The structure is organized as following.
Section 2 describes the modelling of pneumatic system and the design of ARC briefly. Section 3 explains the details of the design of NN including structure, training process of neural net and the NN based ARC method. Experiments are carried out in Section 4. Finally, Section 5 concludes the paper.

2. Adaptive Robust Controller Design

2.1. Dynamic models

In this paper, the pneumatic servo system mainly consists of proportional directional control valve (FESTO MPYE-5-1/4-010B) and a cylinder (FESTO DNC-63-200-P) and Fig.1 shows the schematic diagram of the servo pneumatic system. The whole mathematical model for the pneumatic servo actuator system includes the model of the pneumatic proportional directional control valve which demonstrate the relation between the output voltage and mass flow rate, then model thermodynamic changes in pneumatic cylinder and motion of the whole valve and cylinder system. This paper only introduces the modelling process briefly, for the details of model is demonstrated in [16-18]. The system model in state-space form is written as (1).

\[
\begin{align*}
\dot{x}_1 &= x_2, \\
mx_2 &= \bar{a}(x_3 - x_4) - \theta_1 x_2 - \theta_2 s_f(x_2) + \theta_3 + \bar{f}_o, \\
\dot{x}_3 &= \gamma \frac{R}{V_a} (\bar{m}_{\text{in}} T_s - \bar{m}_{\text{out}} T_a) - \gamma \frac{A}{V_a} x_2 x_3 + \gamma \frac{1}{S_p V_a} \dot{Q}_a + \theta_4 + \hat{d}_{\text{in}}, \\
\dot{x}_4 &= \gamma \frac{R}{V_b} (\bar{m}_{\text{in}} T_s - \bar{m}_{\text{out}} T_b) - \gamma \frac{A}{V_b} x_2 x_4 + \gamma \frac{1}{S_p V_b} \dot{Q}_a + \theta_5 + \hat{d}_{\text{in}}.
\end{align*}
\]

where \(\hat{\theta} = [\theta_1, \theta_2, \theta_3, \theta_4, \theta_5]^T\) are the unknown parameters and \(X = [x_1, x_2, x_3, x_4]^T\) are the states.

![Figure 1](image1.png)

Figure 1. Schematic diagram of servo pneumatic system

![Figure 2](image2.png)

Figure 2. Adaptive robust control schematic for the system

2.2. Design of ARC

The Figure 2 shows the adaptive robust control schematic for the pneumatic system. As shown in Figure 2, the design of ARC is divided into robust control law with backstepping method and adaptation of system parameters. This paper will introduce this part briefly and the details design process is illustrated in [18].

Robust control law design as follows. The Step 1, the expected virtual input pressure \(p_d\) is calculated according to the motion equation of piston that is the first and second equation of (1), semi-definite Lyapunov function and feedback information of position sensors. Step 2, the expected virtual control input \(q_d\) is calculated according to the mass flow rate function that is the last two equations of (1), semi-definite Lyapunov function and feedback information of pressure sensors. Step 3, \(q\) is already obtained, the control input signal \(u\) for the proportional directional control valve could be calculated according to mass flow equation and the relation between the input signal valve and area of valve orifice.

As for the adaptation of system unknown parameters, on-line recursive least squares estimation (RLSE) of parameter \(\theta\) is employed. The RLSE algorithm is limited by projection mapping guaranteed the parameter estimates keep within the closure of the convex set \(\Omega_0\) that is a known bound. Using the
preset adaption rate restricts for a controlled estimation process, the estimated parameters \( \hat{\theta} \) are updated along with the discontinuous projection calculated by RLSE algorithm [8].

3. An intelligent adaptive robust controller

The regulation of control parameters for servo pneumatic system ARC is quiet time consuming and restricts its application. In order to increase the applicability of ARC, a NN based intelligent ARC is proposed. In this approach, NN adapt ARC control parameters online according to feedback errors automatically.

3.1. RBF Neural Network

The Neural Network regulation algorithm is based on the modified back propagation method (MBPM) originated by Lewis[19]. As showed in Figure 3, the basic structure for the NN in that is a three layer neural network. The activation functions for each neuron is a key design deciding the nature of neurons. For radial basic (RBF) NN’s, \( R_j \) called activation function is commonly given as:

\[
R_j(x) = \exp \left( -\frac{||x-c_j||^2}{b_j^2} \right), \quad j = 1, 2, \ldots, N
\]

where \( c_j \) is the center of \( j \)th activation function, \( b_j \) is the width of \( j \)th activation function, \( N \) is the number of nodes in second layer. Input of neural network is defined as a \( n \) dimensional vector \( x = [x_1(t), x_2(t), \ldots, x_n(t)]^T \). And the output is given as:

\[
y_w(t) = \sum_{j=1}^{N} \omega_j(t) R_j(x(t)) + d
\]

where \( \omega_j \) is the weight of \( j \)th element of second layer and \( d \) is bias of second layer.

The target function for Neural Network practice is

\[
E(t) = \sum_{i=1}^{M} e_i^2(t) = \sum_{i=1}^{M} (y_i(t) - y_{w_i}(t))^2 = \sum_{i=1}^{M} \omega_j(t) R_j(x_i(t)) - d
\]

where \( e_i(t) \) is the error and \( y_i(t) \) is the output of real system, \( M \) is the number of data considered for calculation for the system.

To express in matrix form, we define \( y = [y_1, y_2, \ldots, y_M]^T \), \( u = [R_1, R_2, \ldots, R_M, 1]^T \), \( U = [u_1, u_2, \ldots, u_M]^T \), \( \omega = [\omega_1, \omega_2, \ldots, \omega_N, d]^T \). The target function becomes

\[
F(\omega) = (y - U\omega)^T (y - U\omega)
\]

Let regularization and expand the expression can get general form of a quadratic function and the Hessian matrix as \( 2[U^T U + \rho I] \) which is semi-positive or positive [20].

For the regulation of parameters, matrix is supposed to be positive, then the strong minimum is:

\[
\omega = (U^T U + \rho I)^{-1} U^T y
\]

3.2. Parameter selection of activation function

The parameters of neurons affect the effective of neural network greatly. This part explains the selection and computation of neural network.

The parameter \( c \) which means the center of activation function and parameter \( b \) decided the width of activation function play an important role in training process of neural network. According to [20-21], this paper pick the parameter \( c \) according to the orthogonal least squares method that means centers focus on the input data of neural network and \( b \) is chosen as \( b = \frac{1}{\sqrt{n} \text{dist}} \) where \( \text{dist} \) is the average distance between its centers and neighbors.

For the number of neural \( N \) and the number data \( M \) take in for calculation, a trade-off is made between the precision of neural network and calculation efficiency. The Larger the \( N \), \( M \) is, the neural network is more precision for the target function at cost of large computing time. In this paper we set \( N=6 \), \( M=8 \), satisfying the demand of quick computing which is in real time and guaranteed the relative precision.
3.3. NN based ARC

In this section, NN based ARC strategy is proposed and the schematic structure of arithmetic is showed in Figure 4. Define control input is $u$, control parameter is $p$, $e$ is the error between system reference trajectory $r$ and system output $y$, 

$$
\begin{align*}
\dot{x}_j(t) &= e_j(t) - e_j(t-1) \\
\Delta u(t) &= p(t-1) x_j (t)
\end{align*}
$$

(7)

The target function is as (4) and gradient decent method is used for the adaptation process of parameter $p$ as,

$$
\Delta p(t) = -\eta_c \frac{\partial E(t)}{\partial p(t-1)} = -\eta_c \frac{\partial E(t)}{\partial y(t)} \frac{\partial y(t)}{\partial u(t)} \frac{\partial u(t)}{\partial p(t-1)} = \eta_c e_i(t) \frac{\partial y(t)}{\partial u(t)} x_j (t)
$$

(8)

and learning of parameter $p$ is,

$$
p(t) = p(t-1) + \Delta p(t) + \alpha_c (p(t-1) - p(t-2))
$$

(9)

According to (8), $\frac{\partial y(t)}{\partial u(t)}$ (Jacobian matrix) need to be calculated when adapt parameters. Because Jacobian matrix is unknown using RBF NN output instead of real system output, that is

$$
\frac{\partial y(t)}{\partial u(t)} = \sum_{j=1}^{n} \beta_j (t-1) \frac{\partial R_j(x(t))}{\partial u(t)} = \sum_{j=1}^{n} \beta_j (t-1) \partial R_j(x(t)) \frac{c_{j(n+1)}}{b_j^2(t-1)}
$$

(10)

For the pneumatic system, the control parameters and the state of system is described as the following nonlinear extended autoregressive sliding mode,

$$
y(t) = f(y(t-1),...,y(t-n_c); u(t-1),...; u(t-n_u))
$$

(11)

where $u(\bullet), y(\bullet)$ represent output and input of system, and $f(\bullet)$ represents the relation between output and input. $k_1, k_2, k_3$ is the control parameters need to regulate and the adaption of control parameters is on the basis of relation between control parameters and the error defined in ARC as follows,

$$
\begin{align*}
\Delta k_i(t) &= p_i(t-1) x_{s_i} \\
k_i(t) &= p_i(t-1) x_{s_i} + p_i(t-1) x_{s_i}
\end{align*}
$$

(12)

where $x_{s_j} = e_{s_j}(t) - e_{s_j}(t-1)$, $x_{s_m} = e_{s_m}(t) - e_{s_m}(t-1)$, $i=1,2,3$, $e_{s_m} = \frac{1}{10} \max(10) \| e(t) \|_{0\leq t \leq 10}$ is the average value of 10 largest error of during a period of tracking signal.

Taking $k_3$ as an example, the adaptation of control parameter is

$$
\begin{align*}
\Delta p_{31}(t) &= -\eta_c \frac{\partial E(t)}{\partial k_3(t-1)} \\
&= -\eta_c \frac{\partial E(t)}{\partial y(t)} \frac{\partial y(t)}{\partial u(t)} \frac{\partial u(t)}{\partial p(t-1)} \\
&= -\eta_c e_i(t) \frac{\partial y(t)}{\partial u(t)} x_{s_m}
\end{align*}
$$

(13)
Despite the coupling of control parameters, the 3 control parameters $k_1$, $k_2$, $k_3$ which influence the control precision greatly will be regulated simultaneously with the designed NN.

4. Experiment

4.1. Experiment setup
To verify the NN based ARC, an experimental platform is set up. FESTO DNC-63-200-P cylinder is controlled through a FESTO MPYE-5-1/4-010B proportional directional valve. MPX5700AP pressure transducers are used for the measurement of the chamber pressures and the tank pressure. Position of the cylinder movement is acquired by the resistance displacement sensor (KTC-600). Velocity and acceleration are calculated by differential tracking filter. NI PXI 1042Q controller board is used for providing control output.

4.2. Trajectory tracking experiment
The initial value of NN algorithm parameters and ARC control parameters are shown in table 1.

| symbol     | Meaning                                      | value      |
|------------|----------------------------------------------|------------|
| $b_j(0)$   | Initial value activation function parameter  | 1          |
| $c_j(0)$   | Activation function parameter                | Calculated |
| $\omega_j(0)$ | Activation function parameter                | Calculated |
| $N$        | Number of hide layer nodes                   | 6          |
| $M$        | Data for calculation for one time            | 8          |
| $\alpha$   | Momentum factor of regulating parameters     | 0.1        |
| $\eta$     | Learning rate of regulating parameters       | 0.5        |
| $k_1,k_2,k_3$ | Initial value of control parameters $k_1,k_2,k_3$ | $[1,1,1]^T$ |

Figure 5 provides the convergence of parameters $k_1,k_2,k_3$ and $e_1,e_2,e_3$ for NN based Intelligent ARC tracking 0.5Hz sinusoidal wave. It is showed that the parameters $k_1,k_2,k_3$ converge to a steady value in a short time automatically and error $e_1,e_2,e_3$ reduce gradually. Figure 6 shows tracking performance when all the control parameters are steady.

![Figure 5. Convergence of $k_1,k_2,k_3$ and $e_1,e_2,e_3$](image-url)
Figure.6 Tracking responses of $0.09 \sin(0.5\pi t)$ for steady

The experiment can be qualified with the following two indices:

1) $e_{\text{max}} = \max \{ |z| \} |_{T_f - 10 \leq t < T_f}$, the maximum absolute tracking error in last 10 seconds, is measured the final tracking accuracy, where $T_f$ represents the total running time.

2) $\|e\|_{\text{rms}} = \sqrt{\frac{1}{10^{T_f - 10}} \int_{T_f - 10}^{T_f} z_i^2 \, dt}$, the root-mean-square of tracking error, is measured the average tracking accuracy.

5. Conclusion

1) An Intelligent ARC based NN is developed for both strengthening the applicability of pneumatic cylinders and achieving high precision tracking control. Experimental results for sinusoidal trajectory tracking motion are shown in Figure.5 and Figure.6. The experiment illustrates that all three control parameters $k_1$, $k_2$, $k_3$ are converged simultaneously despite the existence of fluctuation caused by the coupling of parameters and disturbance, and good tracking performance is achieved that the relative maximum tracking error is less than 1.5% and root-mean-square error is less than 0.5%.

2) The proposed controller employs on-line NN to regulate the control parameters of ARC automatically with no harm to the control performance of ARC in real time. The method points out how to design a neural network including selection of neural number, calculation of center, width, bias and weight of neural and how to adapt parameters. This method is not constraint of utilizing of ARC for regulation of control parameters if good target function is selected.

3) There are several difficulties to overcome. The valve deadzone properties which restrict the control precision is a vital problem for application of pneumatic system. Even the same batch of valves has different deadzones, but it is unrealistic to measure each one’s deadzone. A method is need to propose to solve this problem. Also friction of pneumatic system should be considered for a higher precision control. A new model or an intelligent method compensate the friction, such as neural network which has been proved effectively for fitting complex model need to be proposed.

6. References

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