Generalized predictive control for DEAP flexible bionic actuator with fuzzy model

Yuan Li*, Jinwen Zheng, Zhaoguo Jiang, Qinglin Wang

School of Automation, Beijing Institute of Technology, Beijing, 100081, China

*Corresponding author

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Abstract

Dielectric electro-active polymer (DEAP) is novel type of flexible smart materials, which have advantages of light weight, high energy density and fast response, making them especially suitable for the actuator material of bionic robots. However, DEAP materials generally have hysteresis effect, creep, uncertainty and nonlinear characteristic, and result in challenges for control strategies. To address this issue, an improved generalized predictive control (GPC) strategy based on T-S fuzzy model is presented in this paper. T-S model is adopted to model for DEAP actuator and GPC controller is developed based on the model. A position tracking experiment was conducted with the DEAP experiment platform. The experimental results show that this control strategy has high tracking accuracy and fast response speed, and the proposed model and control method for EAP flexible actuator were verified. Copyright © 2018 VBRI Press.

Keywords: Smart material, DEAP Actuator, Generalized Predictive Control, T-S model.

Introduction

Bionic robot has been widely researched in recent years as an emerging branch in robotics. Conventional actuators, such as motor, pneumatic and hydraulic actuators, usually have large mass, complex structure and low energy density, and have challenges for driving bionic robots. As a smart material, Dielectric Electro-Active Polymer (DEAP) is attractive because of its low energy consumption, light mass and a larger deformation capability and faster response than conventional materials [1,2]. The advantages of DEAP push its applications in actuators [3,4], especially in the field of bionic robot. However, the actuators with DEAP materials generally have strong hysteresis, creep property, uncertain and nonlinear characteristics, which lead to poor performance of many control strategies. Therefore, this paper is mainly to research the modeling and control of DEAP flexible bionic actuator.

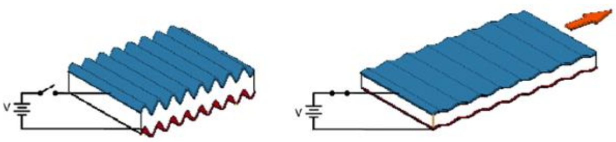
For servo control problem of smart material actuator system, there are two main methods adopted by researchers in recent years. (1) Hysteresis model, such as P model [6,7], PI model [8-10], BW model [11,12], is firstly established, then hysteresis is compensated using an inverse hysteresis model, the system becomes a pseudo-linear system. On this basis, control algorithm is developed; (2) Actuator system with hysteresis nonlinearity is treated as a black box model, controller is designed directly on this model. This paper adopted the second method, to explore a fuzzy approximation of EAP actuator for predictive control.

Aiming at the electromechanical characteristic of DEAP actuator system, a generalized predictive control [13] (GPC) strategy based on T-S model is presented. GPC as a branch of predictive control has become an important control strategy in industrial process, like drum level control system [14], thermal power plant [15]. It has the following characteristics [16]: (1) GPC need few parameters compared with other predictive control algorithm; (2) As developed form adaptive control, GPC has better robust performance while maintaining the advantages of adaptive control; (3) Rolling optimization, feedback correction and multi-step prediction strategy adopted in GPC can effectively overcome the lag in the system. T-S model is a widely used fuzzy model which can express the dynamic of complex system without knowing its actual physical model. The main contributions of the paper is to model the DEAP actuator system with nonlinearity by T-S fuzzy model, and realize the advanced control using the generalized predictive control method with adaptability and robustness.

The remainder of the paper is organized as follows. Section II illustrates the principle of DEAP flexible actuator, and a platform of DEAP actuator for physical experiments. Section III introduces the theory of traditional generalized predictive control Strategy. Section IV develops the improved GPC based on T-S fuzzy model, including the identification of T-S Fuzzy Model using fuzzy c-means and least squares method, and the procedures for design an improved GPC controller. Section V shows and analyzes the simulation results. Finally, the concluding remarks are given and future work plans are presented in section VI.

Principle and platform

The working principle of DEAP material is shown in **Fig.1** [5]. When large actuation voltages (hundreds to thousands V) of opposite polarity are applied to the compliant electrodes, silicon film has a certain potential on both sides, the compliant electrodes will attract each other, a pressure by electrostatic forces is created to compress the polymer film to reduce its thickness, and increase its area at a constant volume, generate a maximum deformation of 30%. DEAP actuator can generate larger actuation force up to 10N.



(a) outage (b) energizing

Fig.1. Working principle of DEAP material.

The experiment platform of DEAP actuator consists of PC, data acquisition card (PCI-1710), high-voltage power supply (S15-3P), LVDT displacement sensor and DEAP actuator, as shown in **Fig. 2**. As an intelligent flexible material, DEAP need a certain amount of tensile force, so in the platform DEAP actuator uses vertical hanging in order to produces a pre-stretching force by the gravity of the actuator. The data acquisition card transfers the displacement signal collected by LVDT sensor to PC using 'analog in' model, and the control signal from PC to high-voltage power supply to stimulate the DEAP actuator using 'analog out' model. The 'analog in' and 'analog out' model is in MATLAB Simulink of PC.

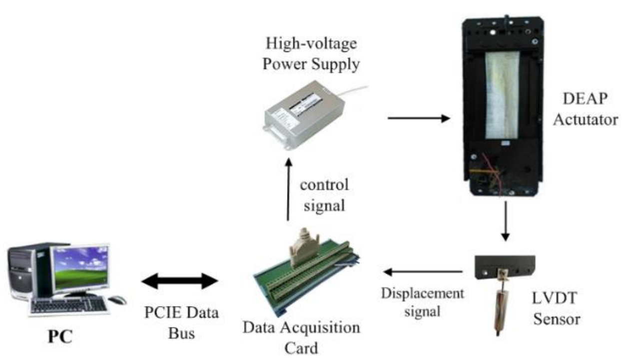


Fig.2 The block diagram of experiment platform.

Generalized predictive control strategy

As an algorithm of Model Predictive Control, Generalized Predictive Control mainly contains three parts: prediction model, rolling optimization and feedback correction, then the optimal control law will be obtained.

GPC uses the following Controlled Auto-Regressive Integrated Moving-Average (CARIMA) Model [1,17] to describe the mathematical model of the controlled plant

$$A(z^{-1})y(t) = B(z^{-1})u(t-1) + C(z^{-1})w(t)/\Delta, \tag{1}$$

where $y(t)$ $y(t)$ and $u(t)$ are the output and input of system; $\Delta = 1 - z^{-1}$ is difference operator; $w(t)$ is white noise with zero mean and satisfies the following equation

$$\begin{cases} E(w(t)|F_{t-1}) = 0, a.s. \\ E(w^2(t)|F_{t-1}) = \sigma^2 \\ \lim\sup_{N\to\infty} \frac{1}{N}\sum_{t=1}^{N} w^2(t) < \infty \end{cases}, \tag{2}$$

where $w(t)$ is a Gauss random sequence. It is generally assumed that the weighted coefficients $\lambda(j) = \lambda$. $A(z^{-1})$, $B(z^{-1})$ and $C(z^{-1})$ are polynomials in the z^{-1}

$$\begin{aligned} A(z^{-1}) &= 1 + a_1 z^{-1} + \cdots + a_{n_a} z^{-n_a} \\ B(z^{-1}) &= 1 + b_1 z^{-1} + \cdots + b_{n_b} z^{-n_b} \\ C(z^{-1}) &= 1 + c_1 z^{-1} + \cdots + c_{n_c} z^{-n_c} \end{aligned}, \tag{3}$$

The expression of the objective function of GPC is defined as

$$J = \sum_{j=N_0}^{N_1} [y(k+j) - w(k+j)]^2 + \sum_{j=1}^{N_u} \lambda(j)[\Delta u(k+j-1)]^2, \tag{4}$$

Where N_1 and N_u are integers, represent the prediction horizon and control horizon respectively. As adjustable parameters of controller, they are determined in the debug of actual application. The problem of GPC strategy is to find the optimal Δu, which is equivalent to solving the following Diophantine equation

$$\begin{aligned} &1 = E_j(z^{-1})A(z^{-1})\Delta + z^{-1}F_j(z^{-1}) \\ &E_j B = G_j + z^{-j}H_j,\ j = 1,\cdots,N \end{aligned}, \tag{5}$$

where the polynomials E_j, F_j, G_j and H_j have the following forms:

$$\begin{cases} E_j(z^{-1}) = e_0 + e_1 z^{-1} + \cdots + e_{j-1} z^{-j+1} \\ F_j(z^{-1}) = f_0^j + f_1^j z^{-1} + \cdots + f_{n_a}^j z^{-n_a} \\ G_j(z^{-1}) = g_0 + \cdots + g_{j-1} z^{-j+1} \\ H_j(z^{-1}) = h_0^j + \cdots + h_{n_b-1}^j z^{-n_b+1} \end{cases}. \tag{6}$$

In order to highlight the essential problem and simplify calculation, assume $C(Z^{-1}) = 1$. Then define the following matrix ($N_1 \ge N_u$).

$$G = \begin{bmatrix} g_0 & & & 0 \\ g_1 & g_0 & & \\ \vdots & & & \\ g_{N_u-1} & g_{N_u-2} & \cdots & g_0 \\ \vdots & & & \\ g_{N_1-1} & g_{N_1-2} & & g_{N_1-N_u} \end{bmatrix} \tag{7}$$

$$\begin{cases} y^T = [y(t+1),\cdots,y(t+N_1)] \\ u^T = [\Delta u(t),\cdots,\Delta u(t+N_u-1)] \\ y_r^T = [y_r(t+1),\cdots,y_r(t+N_1)] \end{cases}. \tag{8}$$

Substituting (7) and (8) into (4), we obtain

$$J = E[(y - y_r)T(y - y_r) + \lambda u^T u | F_t]. \quad (9)$$

To minimize the value of *J*, *u* is obtained

$$u = (G^T G + \lambda I)^{-1} G^T [(y_r - Fy(t) + H\Delta u(t-1)] \quad (10)$$

where the matrix $F = [F_1^T, \cdots, F_{N_1}^T]$. Take the first line of $(G^T G + \lambda I)^{-1} G^T$ as p^T. According to (8) and (10), we obtain

$$\Delta u(t) = p^T [(y_r - Fy(t) + H\Delta u(t-1)]. \quad (11)$$

Diophantine equation is difficult to be solved directly, so it is generally solved by recursive method, as reference [13]. The adjustable parameters of GPC including λ, N_1 and N_u. If system is stable but the control amount varies greatly, λ should be appropriate increased to reduce the control amount. N_1 often takes the rise time of system so that the dynamic of the system can be fully displayed. $N_u \le N_1$, for simple system, $N_u = 1$. When N_u is too large, the sensitivity of control will increase but the robustness will drop.

Improved GPC based on T-S model

The improved generalized predictive control strategy based on T-S model combines the idea of fuzzy and prediction theory, having robustness of predictive control strategy without knowing the physical model of system. This paper discusses the application of T-S model based generalized predictive control on the DEAP actuator. Each rule in the T-S model can be considered as a CARIMA model and the block diagram of the control system is shown in **Fig.3**.

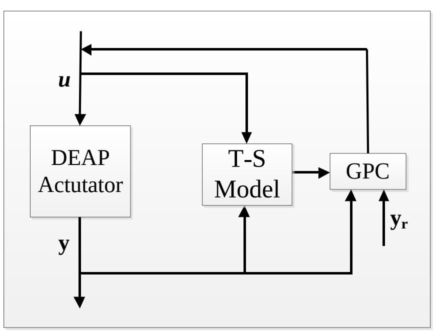


Fig. 3. The diagram of control system.

A typical T-S model of the MISO dynamic system described by N fuzzy rules is as follows

$$\begin{aligned} &R^i : \text{if } x_1 \text{ is } A_1^i, x_2 \text{ is } A_2^i, \cdots, x_m \text{ is } A_m^i \\ &\quad \text{then } y^i = p_0^i + p_1^i x_1 + p_1^i x_1 + \cdots + p_1^i x_1,\ i = 1,2,\cdots,r \end{aligned} \quad (12)$$

where R^i is the i th fuzzy rule; x_i is the i th input variable; A_j^i is fuzzy set corresponding to the j th variable of i th rule; m is the number of input variables; r is the number of rules. y^i is the output variable of i th fuzzy rule; p_j^i is j th output parameter of i th rule. The output of T-S fuzzy system is the weighted average output of each subsystem, this paper applies the central weighted defuzzification method as following

$$y = \frac{\sum_{i=1}^{r} w^i y^i}{\sum_{i=1}^{r} w^i} = \sum_{i=1}^{r} \eta^i y^i, \quad (13)$$

where η^i is the membership of i th rule. The direct product of fuzzy inference uses quadrature method,

$$w^i = \prod_{p=1}^{m} A_p^i(x_p), \quad (14)$$

where $A_p^i(x_p)$ is the membership of x_p belongs to fuzzy set A_p^i. Although each rule of T-S model is linear, it is nonlinear in essential seen from (13) and (14). T-S model can approximate a nonlinear function [18,19] with arbitrary precision, which is also the reason for using the T-S model to model DEAP drive systems.

Parameters identification of T-S model includes the antecedent parameters identification and consequent parameters identification. In this paper, the fuzzy C means clustering method and least square method are applied to identify the antecedent and consequent parameters respectively.

Suppose the input variable dimension of the antecedent of the T-S model is m, and the dimension of output is 1. Firstly, n sampling of system is implemented, denoted by $S = (X_1, X_2, \cdots, X_N)$, where $X_k = (x_{1k}, x_{2k}, \cdots, x_{mk}, y_k)$ is the k th sample, $x_{jk}, j = 1,2,\cdots,m$ is the j th input value of sample of k th sample, y_k is the output value. It is assumed that the sample set S is divided into c categories, that is, the number of fuzzy rules for the T-S model to be established is c. Process of the FCM [20] algorithm is as follows.

First, the objective function is defined as

$$J(U,V) = \sum_{k=1}^{n} \sum_{i=1}^{c} (u_{ik})^p d^2(X_k, V_i), \quad (15)$$

where $V_i (i = 1,2,\cdots,c)$ is the cluster center vector of category i with dimension $m+1$; $p \in (1,\infty)$; matrix $U = [u_{ik}]$ is a fuzzy partition fuzzy partition of sample S, u_{ik} is the membership of sample data X_k belong to cluster center V_i, which satisfies $\sum_{i=1}^{c} u_{ik} = 1$.

The distance function is defined as

$$d(X_k, V_i) = \|X_k - V_i\|_2 = \sqrt{(X_k - V_i)^T (X_k - V_i)}. \quad (16)$$

The FCM clustering is to seek the optimal U and V, so that the objective function J is minimized. The updating method of cluster centers and membership are obtained by optimizing the objective function with Lagrange multiplier [21],

$$\begin{cases} V_i = \dfrac{\sum_{k=1}^{n}(u_{ik})^p X_k}{\sum_{k=1}^{n}(u_{ik})^p} \\ u_{ik} = \dfrac{1}{\sum_{j=1}^{c}(\frac{d_{ik}}{d_{jk}})^{2/(p-1)}} \end{cases} \quad (17)$$

The fuzzy set of the antecedent parameters can be determined after determining the membership center V_i. The membership of antecedent input variable x_j belongs to fuzzy set A_j^i in i th fuzzy rule is expressed by Gauss membership function

$$f^i(x_j) = \exp[-(\frac{x_j - V_{ij}}{\sigma_i})^2], i = 1,2,\cdots,c; j = 1,2,\cdots,m, \quad (18)$$

where σ_i is the width of membership function, and σ_i is determined by the following k-nearest neighbor algorithm

$$\sigma_i = \frac{1}{\beta}(\frac{1}{k}\sum_{l=1}^{k}\|V_i - V_j\|_2), \quad (19)$$

k generally takes 1 or 2 when the number of rules is small; β is constant.

The consequent parameters are identified by the least square method. By minimizing the sum of error square to find the best matching parameters, the least square method is widely used in curve fitting, parameter estimation and other fields with a very good effect. Suppose the number of samples used for identification is l, and $l < n$. Other samples are used to test the generalization performance of model. The identified parameters can be written in vector form as follows

$$\theta = [p_0^1, p_1^1,\cdots, p_m^1, p_0^2, p_1^2,\cdots, p_m^2, p_0^c, p_1^c,\cdots, p_m^c,]. \quad (20)$$

According to (13) and (14), the output estimation of j th sample X_j corresponding to T-S model is

$$\hat{y}_j = ([\eta_j^1, \eta_j^2,\cdots,\eta_j^c] \otimes [1, x_{1j}, x_{2j},\cdots, x_{mj}])\theta = \phi_j^T\theta. \quad (21)$$

where $\otimes$ is Kronecker product, η_j^k is the membership of X_j in k th rule. We obtained from (13), (14) and (18) that

$$\eta_j^k = \frac{w^k}{\sum_{k=1}^{c} w^k} = \frac{\prod_{i=1}^{m} f^k(X_{ij})}{\sum_{k=1}^{c}\prod_{i=1}^{m} f^k(X_{ij})}. \quad (22)$$

The output vector used to model is defined as $Y = [y_1, y_2,\cdots, y_l]^T$, and corresponding estimated output vector of model is $\hat{Y} = [\hat{y}_1, \hat{y}_2,\cdots,\hat{y}_l]^T$, model error vector is denoted as $E = Y - \hat{Y}$. Using (21), we obtain

$$[\phi_1, \phi_2,\cdots,\phi_l]^T\theta = \hat{Y}, \quad (23)$$

When the antecedent parameters identification is completed, the least square method is used to estimate consequent parameters of (23).

Consider the following system:

$$y = a_1x_1 + a_2x_2 + \cdots + a_nx_n, \quad (24)$$

where y is the system output, x_i is system input, a_i is unknown constant. Let $\hat{y}$ indicate the measured value of y. Assuming that the system is sampled m times, the corresponding input and output is denoted as $\hat{y}(m)$, $x_i(m)$, the output error is defined $e(m) = y(m) - \hat{y}(m)$. Written in matrix form

$$\begin{bmatrix} x_1(1) & x_2(1) & \dots & x_n(1) \\ x_1(2) & x_2(2) & \dots & x_n(2) \\ \dots & & & \\ x_1(m) & x_2(m) & \dots & x_n(m) \end{bmatrix} \begin{bmatrix} a_1 \\ a_2 \\ \dots \\ a_n \end{bmatrix} = \begin{bmatrix} \hat{y}(1) \\ \hat{y}(2) \\ \dots \\ \hat{y}(m) \end{bmatrix} + \begin{bmatrix} e(1) \\ e(2) \\ \dots \\ e(m) \end{bmatrix}. \quad (25)$$

Denote (25) simply as $Xa = \hat{y} + e$, the symbols are corresponding to (13). The least squares method uses the observed data to estimate the parameter a, which is equivalent to the following optimal problem:

$$\min_a e^T e. \quad (26)$$

The estimated parameters are $\hat{a} = \arg\{\min_a e^T e\}$, and the cost function is $J = e^T e$.By (25),

$$\begin{aligned} J(a) &= (Xa - \hat{y})^T(Xa - \hat{y}) \\ &= a^T X^T Xa - 2a^T X^T\hat{y} + \hat{y}^T\hat{y} \end{aligned}. \quad (27)$$

By the calculus knowledge, the condition that J takes extreme value is $\frac{\partial J}{\partial a} = 0$. Substitution it to (15) and obtain that

$$\frac{\partial J}{\partial a} = 2X^T Xa - 2X^T\hat{y} = 0. \quad (28)$$

If the matrix $X^T X$ is non-singular, the estimated value of $\hat{a}$ is as follows with (28)

$$\hat{a} = (X^T X)^{-1} X^T\hat{y}. \quad (29)$$

Least squares method is applied to the system (23). Denote the matrix $\Phi = [\phi_1, \phi_2,\cdots,\phi_l]^T$, then the estimated parameters can be obtained from (23) and (29)

$$\hat{\theta} = (\Phi^T\Phi)^{-1}\Phi^T Y. \quad (30)$$

Then the output of T-S based system is determined by the following equation

$$\Delta u(t) = \sum_{i=1}^{n}\eta^i\Delta u^i(t), \quad (31)$$

where $\Delta u^i(t)$ is the control increment calculated according to CARIMA model of rule and GPC algorithm.

Experiments and results

The selection of input vector dimensions has a great influence on the model. Large dimension will increase the computation and reduce the response speed; small dimension will make the T-S model cannot express the system well with a large model error. In this paper, under specific condition and repeated debugging, the sample vector are chosen as $[y(k-1), y(k-2), u(k-1), u(k-2), y(k)]$, where $y(k)$ is the sample displacement value of kth sample period of DEAP actuator system. The sampling period is set to T=0.01s.

The sample number is 8000 of which the first 6000 samples were used for parameter identification of T-S model, 2000 samples for T-S model identification. The input excitation signal is combination of an uniformly distributed random signal between [0, 0.5] and a square wave signal (the period is 20s and the amplitude is 1). The reason for choosing random signals as input is that it ensures that enough information is available to the identified samples in order to identify more accurate parameters.

The parameter setting of fuzzy C-mean is shown in **Table 1**. After system identification, cluster centers are shown in **Table 2**. The cluster center is the antecedent parameter of fuzzy rules, and the results of the consequent parameters are identified by the least square method: [0.0308, 0.0621, 1.9416, -0.9706, -0.0133, 0.0239, 1.8861, -0.8884, 0.0308, 0.0370, 1.9119, -0.9460].

Table 1. Parameter setting of the fuzzy C-mean.

Parameter	value
c(rule number)	3
p	2
β	2
k	1

Table 2. List of cluster centers.

	x_1	x_2	x_3	x_4	x_5
Rule 1	1.724	1.724	4.081	4.097	4.097
Rule 2	0.759	0.758	1.062	1.062	1.062
Rule 3	1.745	1.745	4.883	4.867	4.864

The result of model identification is shown in **Fig. 4,** where the dotted line represents the actual output of the system, and the solid line represents the estimated output of the T-S model. It can be seen that the model error amplitude is generally controlled in 0.1, while the output amplitude is about 5, that is, the relative error of the model is about 2%. **Fig. 5** shows the results comparing the output between actual system and T-S model with non-train samples. As can be seen from the figures, the magnitude of the model error is still within 0.1. As a whole, the established T-S model can describe the DEAP drive system well.

The parameters of generalized predictive control are set to $N_1=7$, $N_u=1$ and $\lambda_1=6$. The simulation results are shown in fig.6. The dotted line indicates the reference input and the solid line represents the system output. As can be seen from fig.4, the steady state error of the system is about 0, and adjustment time is about 1s. That is, the generalized predictive control based on T-S model has high tracking accuracy and response speed in DEAP actuator system control. From **Fig.4**, the system tracking curve is very smooth, almost no jitter, which further illustrates the DEAP actuator the advantages of little noise, which is not possessed by general motor drives.

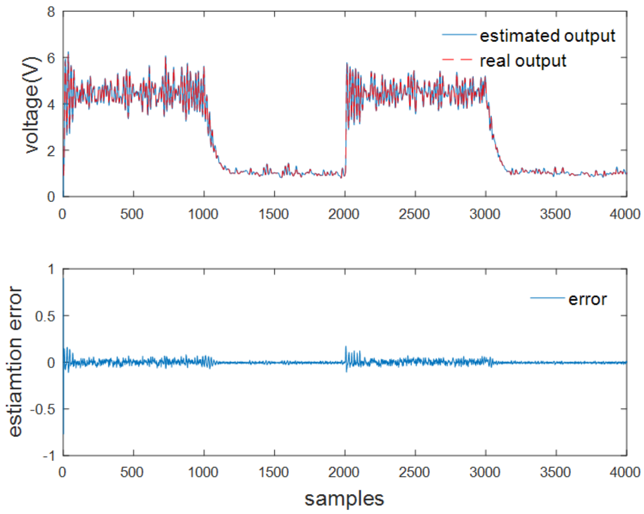


Fig. 4. Comparison between real output and T-S model output.

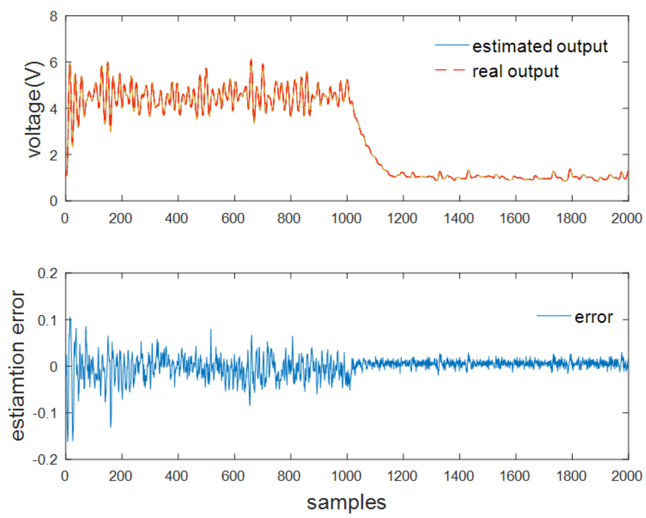


Fig. 5. The generalization performance of the T-S model.

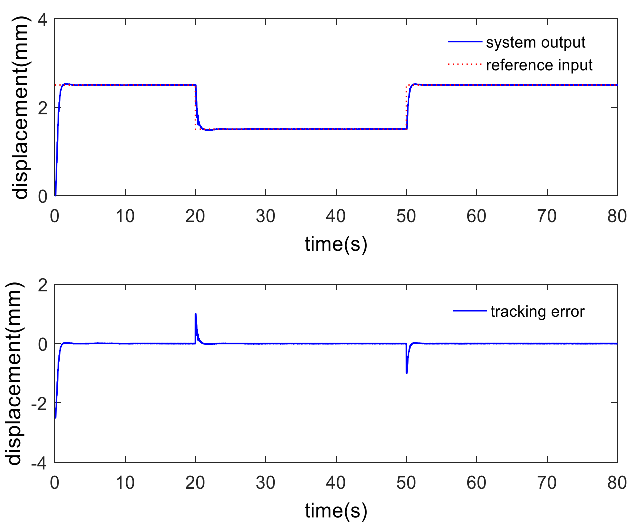


Fig. 6. Comparison between system output and reference input.

Conclusion

In this paper the generalized predictive control based on T-S fuzzy model is applied to servo control of the DEAP actuator system. First, the relationship between input voltage and output displacement of DEAP actuator is established. The experimental results show that the model error can be controlled at about 2% compared with the physical system. Furthermore, the un-modeled sample data is used for verification. On this basis, the control value is calculated on each rule of T-S model by generalized predictive control, then the actual control of system is weighted average of the control value corresponding to each rule. The weight coefficient adopts the membership for fuzzy rules. The experimental results show that this control strategy has high tracking accuracy and response speed in DEAP actuator system.

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