Acta Technica *62* (2017), No. 6A, 135–144

Subspace identification for a twin rotor MIMO system based on LPV system

She Minghong[1, 2]

Abstract. To improve identification precision and identification computation efficiency of subspace model of Twin Rotor MIMO System and acquire simplification modeling of model of Twin Rotor MIMO System, the paper puts forward a Twin Rotor MIMO System subspace model identification method based on LPV system. Firstly, by correlation function estimation and following null space projection and giving closed loop subspace identification model and block matrix filling method, acquire scope of extension observability matrix; secondly, based on the same projection of relevant data on time migration set and least squares, acquire dynamics estimation of unknown equipment system model; finally, by identification result contrast experiment on model of folded wing deformed Twin Rotor MIMO System, displays that proposed method can better approach original model effectively and has higher identification precision and identification efficiency, which verifies effectiveness of proposed method.

Key words. Subspace identification, LPV system, MIMO system, correlation function..

1. Introduction

As a kind of optimal control algorithm with stronger industrial application background, model estimation control has the characteristics of better control performance, strong robustness and efficient disposal to multivariable restriction problem [1, 9–10, 21]. Therefore, it is widely used in process control in fields of petroleum and electricity.

Predictive control algorithm is put forward aiming at liner system originally. Because actual deviation of output prediction by adopting liner model is relatively large and the purpose of optimal control cannot be reached, therefore, prediction and optimization shall be based on nonlinear model. At present, widely researched nonlinear modeling methods include: mechanism model, Volterra model, Hammerstein model and Wiener model. Establishing mechanism model requires thorough understanding for controlled object [2, 11–13]. However, if production process and technology is complex and connected factors are considerable, the difficulty of es-

[1]School of Automation, Chongqing University, Chongqing, China
[2]Computer College, Chongqing College of Electronic Engineering, Chongqing, China

tablishment of mechanism model is usually large. Special models, such as Volterra model, Hammerstein model and Wiener model require large-scale device test and identification cost is high. Living examples of industry application are fewer compared with liner MPC and nonlinear MPC. The maximal problems are high cost of nonlinear process modeling and identification. Therefore, it is very essential to find a kind low-cost nonlinear modeling method [15].

In the past twenty years, Subspace Model Identification (SMI) has obtained wide public concern, which not only lies in the excellent convergence and simplicity of numerical computation, but also lies in that it better adapts to estimation, prediction and control algorithm. In reference literatures in early period, most subspace identification method has open cycle identification characteristics. In consideration of stability, safety and identification problems facing control, researchers always try to apply these subspace methods to closed loop identification. Huang H and Yang K [3] expands subspace method to frequency response function estimation and confirms continuous and discrete time model by auxiliary variable. Rotondo D and Cristofaro A [4, 16–18] puts forward two methods for frequency statistics characteristics and subspace convergence. For external-input linear closed-loop system that is irrelevant with observed noise, cross-correlation function of output and external-input signal is equal to cross-correlation function of output and external-input signal of dynamic system. Therefore, the relationship between two correlation functions sequences can be absolutely confirmed and unbiased parameter estimation under any noise characteristics can be acquired [23]. Take advantage of sequence of characteristic correlation function sequence as interface function. Carrying important information is hidden in compressive correlation function form in data series. Provide basis for parameter identification by extracting the parameter interface function information.

The paper puts forward a kind of new subspace identification algorithm based on estimation of correlation function aiming at identification problem for Twin Rotor MIMO System to acquire unbiased parameter estimation of linear invariant system dynamics under closed loop condition. Solution is to use translation invariance of dynamic system to realize estimation of correlation function [5, 19].

2. LPV system model for twin rotor mimi system

2.1. LPV model identification for operation track

Object of research in the paper is z-type folded-wing deformed Twin Rotor MIMO System; see Fig. 1. Consider the following LPV system of Multiple Input and Single Output (MISO):

$$\boldsymbol{y}(t) = \boldsymbol{G}_1(q,w)\boldsymbol{u}_1(t) + \cdots + \boldsymbol{G}_p(q,w)\boldsymbol{u}_\rho(t) + \boldsymbol{v}(t)\,, \tag{1}$$

$$\boldsymbol{G}_i(q,w) = \frac{\boldsymbol{B}_i(q,w)}{\boldsymbol{A}_i(q,w)} = \frac{[b_1^i(w)q^{-1} + \cdots + b_n^i(w)q^{-n}]q^{-d_i}}{1 + a_1^i(w)q^{-1} + \cdots + a_n^i(w)q^{-n}}\,, \tag{2}$$

Where, $\boldsymbol{G}_i(q,w)$ is process model from inputting $\boldsymbol{u}_i(t)$ to outputting $\boldsymbol{y}(t)$. $\boldsymbol{v}(t)$ is unmeasured output disturbance and is random process variable with zero mean and bounded variance. $\boldsymbol{w}(t)$ is called as dispatching variable, which decides working point of process operation and $\boldsymbol{w}(t) \in [w_{lo}, w_{hi}]$. Assumed that $\boldsymbol{\theta}(w)$ means parameter vector of process model $\boldsymbol{G}_1(q), \cdots, \boldsymbol{G}_p(q)$, namely:

$$\begin{aligned}\boldsymbol{\theta}(w) = [&a_1^1(w), \cdots, a_n^1(w), b_1^1(w), \cdots, b_n^1(w),\\ &\cdots, a_1^p(w), \cdots, a_n^p(w), b_1^p(w), \cdots, b_n^p(w)]^T .\end{aligned} \tag{3}$$

In classic literatures, carry out parameterization to vector $\boldsymbol{\theta}(w)$ to polynominal function of dispatching variables and then estimate model parameter by making use of least square method. For complex process, there are many problems for this kind of method. Firstly, it requires long-time test in working point of the whole scope, which is generally not permitted. Recursive least squares algorithm adopts ARX model [6]. It widely acknowledged that low-order ARX model will lead to biased estimation, but high-order ARX model causes excessive estimated parameters.

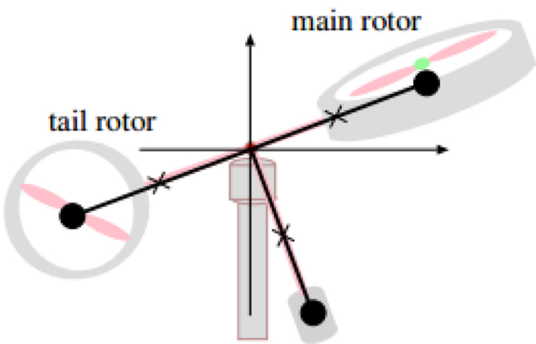

Fig. 1. Model for folded-wing deformed Twin Rotor MIMO System

2.2. Definition of LPV system

LPV system refers to form with linear system [22]. Some systems that change with change of external parameters in system are expressed as follows in the form of state space:

$$\begin{cases}\dot{\boldsymbol{x}} = \boldsymbol{A}(\theta)\,\boldsymbol{x} + \boldsymbol{B}(\theta)\,\boldsymbol{u}\,,\\ \dot{\boldsymbol{y}} = \boldsymbol{C}(\theta)\,\boldsymbol{x} + \boldsymbol{D}(\theta)\,\boldsymbol{u}\,,\end{cases} \tag{4}$$

Where, $\boldsymbol{x}, \boldsymbol{u}, \boldsymbol{y}$ respectively are system state, control input and measurement output; $\boldsymbol{\theta}(w)$ is variable parameter vector, namely $\boldsymbol{\theta} = [\theta_1, \theta_2, \cdots, \theta_n]^T$. For LPV system, all variable parameters are measureable; at the same time, for actual system, assumed that variable parameter and its rate of change has boundary [7].

3. Closed-loop subspace identification based on estimation of correlation function

By correlation function estimation and following null space projection, carry out filling to block matrix of frame of identification to acquire scope of observability matrix, which is basic step to subspace identification method [8]. Then, dynamics estimation of an unknown equipment system model can be gotten based on same projection on time deviant set of relevant data [20].

3.1. Data estimation equation of block matrix

Establish correlation function and estimate block Hankel matrix of $\hat{\boldsymbol{R}}^{yr}_{\tau_0|\tau_{i-1}}$ and $\hat{\boldsymbol{R}}^{ur}_{\tau_0|\tau_{i-1}}$ including i row and j line and specific definition is as follows:

$$\hat{\boldsymbol{R}}^{yr}_{\tau_0|\tau_{i-1}} = \begin{bmatrix} \hat{\boldsymbol{R}}_{yr}(\tau_0) & \hat{\boldsymbol{R}}_{yr}(\tau_1) & \cdots & \hat{\boldsymbol{R}}_{yr}(\tau_{j-1}) \\ \hat{\boldsymbol{R}}_{yr}(\tau_1) & \hat{\boldsymbol{R}}_{yr}(\tau_2) & \cdots & \hat{\boldsymbol{R}}_{yr}(\tau_j) \\ \vdots & \vdots & \ddots & \vdots \\ \hat{\boldsymbol{R}}_{yr}(\tau_{i-1}) & \hat{\boldsymbol{R}}_{yr}(\tau_i) & \cdots & \hat{\boldsymbol{R}}_{yr}(\tau_{j+i-2}) \end{bmatrix}, \tag{5}$$

$$\hat{\boldsymbol{R}}^{ur}_{\tau_0|\tau_{i-1}} = \begin{bmatrix} \hat{\boldsymbol{R}}_{ur}(\tau_0) & \hat{\boldsymbol{R}}_{ur}(\tau_1) & \cdots & \hat{\boldsymbol{R}}_{ur}(\tau_{j-1}) \\ \hat{\boldsymbol{R}}_{ur}(\tau_1) & \hat{\boldsymbol{R}}_{ur}(\tau_2) & \cdots & \hat{\boldsymbol{R}}_{ur}(\tau_j) \\ \vdots & \vdots & \ddots & \vdots \\ \hat{\boldsymbol{R}}_{ur}(\tau_{i-1}) & \hat{\boldsymbol{R}}_{ur}(\tau_i) & \cdots & \hat{\boldsymbol{R}}_{ur}(\tau_{j+i-2}) \end{bmatrix}, \tag{6}$$

Where, every element of $\hat{\boldsymbol{R}}^{yr}_{\tau_0|\tau_{i-1}} \in \mathcal{R}^{n_y i \times n_r j}$, $\hat{\boldsymbol{R}}^{ur}_{\tau_0|\tau_{i-1}} \in \mathcal{R}^{n_u i \times n_r j}$, $\hat{\boldsymbol{R}}^{yr}_{\tau_0|\tau_{i-1}}$ and $\hat{\boldsymbol{R}}^{ur}_{\tau_0|\tau_{i-1}}$ is correlation function data; i and j is user-defined subscript. According to formula (5), above matrix meets the following relationship:

$$\hat{\boldsymbol{R}}^{yr}_{\tau_0|\tau_{i-1}} = \boldsymbol{\Gamma} \boldsymbol{R}^{xr}_{\tau_0} + \boldsymbol{T}_{0|i-1} \hat{\boldsymbol{R}}^{ur}_{\tau_0|\tau_{i-1}}, \tag{7}$$

Where, vector $\boldsymbol{R}^{xr}_{r0}$ is constituted by data of state cross-correlation function:

$$\boldsymbol{R}^{xr}_{r0} = \begin{bmatrix} \boldsymbol{R}_{xr}(\tau_0) & \boldsymbol{R}_{xr}(\tau_1) & \cdots & \boldsymbol{R}_{xr}(\tau_{j-1}) \end{bmatrix}. \tag{8}$$

Therefore, extension measurement matrix and lower triangular block Toeplitz matrix are respectively defined as follows:

$$\boldsymbol{\Gamma} = \begin{bmatrix} \boldsymbol{C}_p & \boldsymbol{C}_p \boldsymbol{A}_p & \cdots & \boldsymbol{C}_p \boldsymbol{A}_p^{i-1} \end{bmatrix}^T, \tag{9}$$

$$\boldsymbol{T}_{0|i-1} = \begin{bmatrix} \boldsymbol{D}_p & 0 & \cdots & 0 \\ \boldsymbol{C}_p \boldsymbol{A}_p & \boldsymbol{D}_p & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ \boldsymbol{C}_p \boldsymbol{A}_p^{i-2} \boldsymbol{B}_p & \boldsymbol{C}_p \boldsymbol{A}_p^{i-3} \boldsymbol{B}_p & \cdots & \boldsymbol{D}_p \end{bmatrix}. \tag{10}$$

By adopting single-step displacement process, corresponding displacement formula of formula (10) can be defined as:

$$\hat{\boldsymbol{R}}^{yr}_{\tau_1|\tau_i} = \boldsymbol{\Gamma} \boldsymbol{A}_p \boldsymbol{R}^{xr}_{\tau_0} + \boldsymbol{T}_{0|i} \hat{\boldsymbol{R}}^{ur}_{\tau_0|\tau_i} , \tag{11}$$

Where, matrix $\boldsymbol{T}_{0|i}$ can be obtained by supplementing on left side of $\boldsymbol{T}_{0|i-1}$ with a list of null points; form is as follows:

$$\boldsymbol{T}_{0|i} = \begin{bmatrix} 0 & \boldsymbol{D}_p & 0 & \cdots & 0 \\ 0 & \boldsymbol{C}_p \boldsymbol{A}_p & \boldsymbol{D}_p & \cdots & 0 \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ 0 & \boldsymbol{C}_p \boldsymbol{A}_p^{i-2} \boldsymbol{B}_p & \boldsymbol{C}_p \boldsymbol{A}_p^{i-3} \boldsymbol{B}_p & \cdots & \boldsymbol{D}_p \end{bmatrix} . \tag{12}$$

Similarly, $\hat{\boldsymbol{R}}^{ur}_{\tau_0|\tau_i}$ expression form can be obtained by adding a line of null points on the bottom of $\hat{\boldsymbol{R}}^{ur}_{\tau_0|\tau_{i-1}}$.

3.2. Estimation of system dynamics

Direct result obtained from Definition 1: for same projection $\prod^{ur}_{\tau_0|\tau_i}$, making use of right projection of formula (5) and formula (8) to remove fixed item including $\boldsymbol{T}_{0|i-1}$ and $\boldsymbol{T}_{1|i}$ from $\hat{\boldsymbol{R}}^{yr}_{\tau_0|\tau_{i-1}}$ and $\hat{\boldsymbol{R}}^{yr}_{\tau_0|\tau_i}$, so, it can be got that:

$$\hat{\boldsymbol{R}}^{yr}_{\tau_0|\tau_{i-1}} \prod{}^{ur}_{\tau_0|\tau_i} = \boldsymbol{\Gamma} \boldsymbol{R}^{xr}_{\tau_0} \prod{}^{ur}_{\tau_0|\tau_i} , \tag{13}$$

$$\hat{\boldsymbol{R}}^{yr}_{\tau_1|\tau_i} \prod{}^{ur}_{\tau_0|\tau_i} = \boldsymbol{\Gamma} \boldsymbol{A}_p \boldsymbol{R}^{xr}_{\tau_0} \prod{}^{ur}_{\tau_0|\tau_i} . \tag{14}$$

Therefore, estimation of extension measurement matrix $\boldsymbol{\Gamma}$ can be got from singular value decomposition on right side of formula (14); computation form is:

$$\hat{\boldsymbol{R}}^{yr}_{\tau_0|\tau_{i-1}} \prod{}^{ur}_{\tau_0|\tau_i} = \begin{bmatrix} \boldsymbol{U}_n & \boldsymbol{U}_s \end{bmatrix} \begin{bmatrix} \sum_n & 0 \\ 0 & \sum_s \end{bmatrix} \begin{bmatrix} \boldsymbol{V}^T_n \\ \boldsymbol{V}^T_s \end{bmatrix} , \tag{15}$$

$$\hat{\boldsymbol{\Gamma}} = \boldsymbol{U}_n \sum{}^{1/2}_n . \tag{16}$$

According to formula (15) and (16), solution of least square of minimization problem is as follows:

$$J = \arg\min_{\boldsymbol{A}_p} \left\| \boldsymbol{A}_p \boldsymbol{\Gamma}^{\dagger} \hat{\boldsymbol{R}}^{yr}_{\tau_0|\tau_{i-1}} \prod{}^{ur}_{\tau_0|\tau_i} - \boldsymbol{\Gamma}^{\dagger} \hat{\boldsymbol{R}}^{yr}_{\tau_1|\tau_i} \prod{}^{ur}_{\tau_0|\tau_i} \right\| , \tag{17}$$

$$\hat{\boldsymbol{A}}_p = \sum{}^{-1/2}_n \boldsymbol{U}^T_n \hat{\boldsymbol{R}}^{yr}_{\tau_1|\tau_i} \prod{}^{ur}_{\tau_0|\tau_i} \boldsymbol{V}_n \sum{}^{-1/2}_n . \tag{18}$$

System matrix $\boldsymbol{C}_p$ can be computed by front n_y lines of extension measurement matrix and specific form is:

$$\hat{\boldsymbol{C}}_p = \hat{\boldsymbol{\Gamma}}\,(1 : n_y, :)\,. \tag{19}$$

Based on estimation to $\boldsymbol{A}_p$ and $\boldsymbol{C}_p$, where whole problem is linear in unknown $\boldsymbol{B}_p$ and $\boldsymbol{D}_p$, therefore, estimation form of output $\boldsymbol{y}\,(k)$ is:

$$\begin{aligned}\hat{\boldsymbol{y}}(k) &= \hat{\boldsymbol{C}}_p\hat{\boldsymbol{A}}_p\hat{\boldsymbol{x}}(0) + (\boldsymbol{u}(k)^T \otimes \boldsymbol{I}_{n_y})vec(\hat{\boldsymbol{D}}_p) \\ &+ (\sum_{t=0}^{k-1} \boldsymbol{u}(k)^T \otimes \hat{\boldsymbol{C}}_p\hat{\boldsymbol{A}}_p^{k-t-1})vec(\hat{\boldsymbol{B}}_p)\,,\end{aligned} \tag{20}$$

Where, estimation of $\boldsymbol{B}_p$ and $\boldsymbol{D}_p$ can be acquired by linear least squares method:

$$\min_{\boldsymbol{B}_p,\boldsymbol{D}_p} \frac{1}{N}\sum_{k=0}^{N-1} \left\|\boldsymbol{y}(k) - \boldsymbol{\varphi}^T(k)\boldsymbol{\theta}\right\|_2^2, \tag{21}$$

Where, $\boldsymbol{\varphi}^T(k) = [(\boldsymbol{u}(k)^T \otimes \boldsymbol{I}_{n_y})(\sum_{k=0}^{s-1} \boldsymbol{u}(k)^T \otimes \hat{\boldsymbol{C}}_p\hat{\boldsymbol{A}}_p^{k-s-1})]$, $\boldsymbol{\theta} = [vec(\hat{\boldsymbol{D}}_p)vec(\hat{\boldsymbol{B}}_p)]^T$.

3.3. Algorithm steps

Specific computational process of closed-loop subspace identification algorithm in the paper is shown as Fig. 2. Firstly, obtain closed-loop prediction to $\boldsymbol{\Gamma}\hat{\boldsymbol{L}}$ and $\hat{\boldsymbol{G}}$ based on subspace projection method. Then, acquire $\hat{\boldsymbol{X}}$, $\boldsymbol{A}$, $\boldsymbol{C}$ and $\hat{\boldsymbol{R}}$ based on matrix operations and singular value decomposition process; finally, solve system parameter matrix $\boldsymbol{B}$ and $\boldsymbol{D}$ by least square.

In Fig. 2, acquisition of $\hat{\boldsymbol{\Gamma}}$ can be obtained by computation of formula (28), $\hat{\boldsymbol{L}}$ can be obtained by computation of formula (33–34) and $\hat{\boldsymbol{T}}$ can be got from formula (16). $\hat{\boldsymbol{X}}$ is state vector matrix of equipment; $\boldsymbol{A}$, $\boldsymbol{B}$, $\boldsymbol{C}$ and $\boldsymbol{D}$ are state space matrix; see Section 2.3 estimation part of system dynamics for computation process; $\hat{\boldsymbol{R}}$ can be got from formula (17).

4. Simulation research

Compare established LPV model with original nonlinear model response; set original state as airspeed 25 m/s and trim state with folding angle θ_r as 0°; wing will be folded in the rate of 20°/s in 2 s after simulation; wing will be folded in the rate of 20°/s in 8 s after simulation and will remain 2 s. Response of all vectors is obtained as shown in Fig. 3–Fig. 5.

It can be seen from Fig. 3–Fig. 5, established LPV model is very close to original nonlinear model response; response errors of angle of incidence and elevation are both less than 0.50; response error of airspeed is less than 1 m/s; therefore, modeling method in the paper is feasible. If decreasing linearization section interval, modeling error can be further decreased.

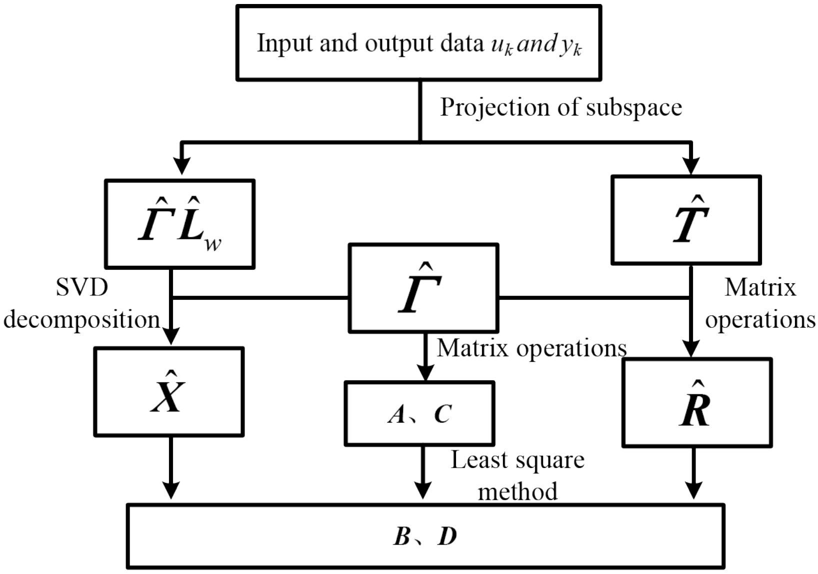

Fig. 2. Subspace identification process of closed-loop data

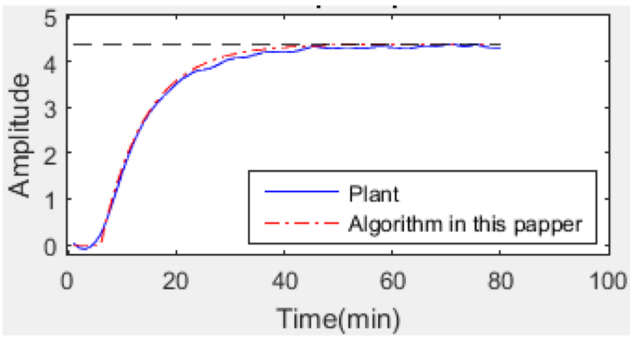

Fig. 3. Response curve of angle of pitch

Select two evaluation indexes of identification precision and identification time; contrast algorithm selects nonlinear identification method and neural network identification method. See Table 1 for experiment result.

Table 1. Performance contrast for algorithm identification

Evaluation index	Nonlinear identification method	Neural network identification method	Algorithm in the paper
Identification precision	1e-1	1e-2	1e-4
Identification time	15.3 s	36.8 s	8.4 s

According to experiment correlation data in Table 1, identification precision of the paper if 1e-4; this precision is higher than nonlinear identification method and neural

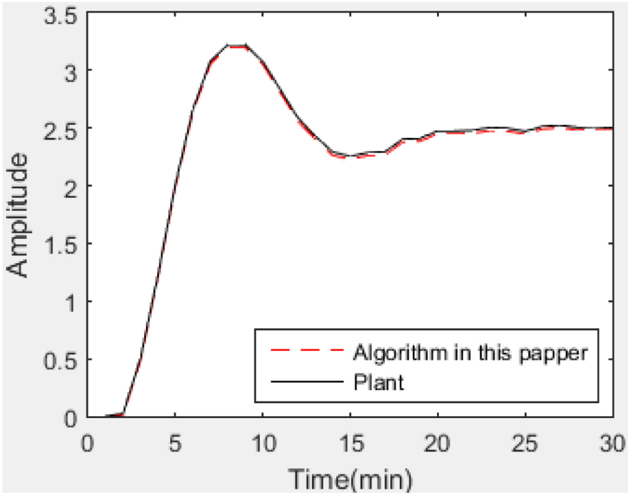

Fig. 4. Response curve of angle of incidence

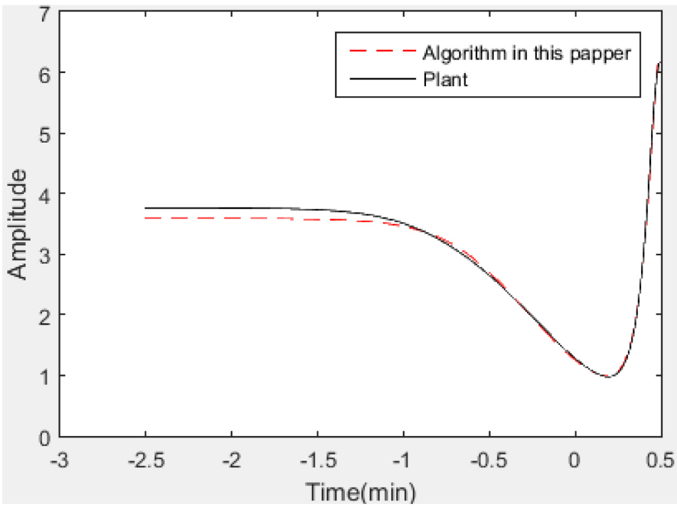

Fig. 5. Response curve of airspeed

network identification method, which is 1e-1 and 1e-2 respectively. However, for identification time index, method of least square is used in nonlinear identification, thus, the computing time is longer while neural network structure is used in neural network identification method and the computing time is very long since it involves cyclic iterative learning with mean 36.8 s required. Compared with two kinds of contrast algorithms, the proposed algorithm in this paper is superior to the contrast algorithms in convergence accuracy and speed, which shows effectiveness of proposed method.

5. Conclusion

In this paper, a kind of method of Twin Rotor MIMO System subspace model identification based on LPV system is proposed. Extension observability matrix scope of has been acquired though correlation function estimation and the following null space projection. Then, dynamical estimation of unknown equipment system model is acquired though least square operation. Stimulation experiment has verified effectiveness of proposed method. Next, closed-loop system control problem of Twin Rotor MIMO System with combination of proposed subspace identification method will be researched mainly.

Acknowledgement

Supported by the Science and Technology Research Program of Chongqing Municipal Education Commission (Grant No.KJ1729403);National Natural Science Foundation of China(No. 61403055); the Fundamental Research Funds for the Central Universities (Grant No. CDJXS12 17 11 01); Chongqing Education Science and planning issues, project name: The Current Situation Analysis and Countermeasure Research of Modern Apprenticeship Practice in Vocational Colleges(No. 2017-GX-422); the Intelligent Robot Technology Research Center of Chongqing College of Electronic Engineering(No.XJPT201705);Chongqing Science and Technology Communication and Popularization Project(No.cstc2017kp-ysczA0021).

References

[1] M. Bartels, Q. Liu, G. Kaiser: *LPV torque vectoring for an electric vehicle using parameter-dependent Lyapunov functions.* (2013), 2153–2158.

[2] M. Q. Nguyen, J. M. G. D. Silva, O. Sename: *A state feedback input constrained control design for a 4-semi-active damper suspension system: a quasi-LPV approach.* Ifac Papersonline, *48* (2015), No. 14, 259–264.

[3] H. Huang, K. Yang, W. Qin: *PD-RMPC for a flexible air-breathing hypersonic vehicle with input saturation and state constraints.* Guidance, Navigation and Control Conference. IEEE, (2014), 1224–1229.

[4] D. Rotondo, A. Cristofaro, T. A. Johansen: *Icing detection in twin rotor MIMO systems with longitudinal motion using an LPV unknown input observer.* (2015), 984–989.

[5] H. Tanaka, Y. Ohta, Y. Okimura: *A local approach to LPV-identification of a twin rotor MIMO system.* IFAC Proceedings Volumes *44* (2011), No. 1, 7749–7754.

[6] A. Wei, X. Hu, Y. Wang: *Consensus of linear multi-agent systems subject to actuator saturation.* International Journal of Control Automation & Systems *11* (2013), No. 4, 649–656.

[7] P. Van Overschee, B. L. De Moor: *Subspace identification for linear systems: Theory, implementation and applications.* Springer Science & Business Media, 2012.

[8] J. Wang, D. Miller, H. W. Wang: *Closed-loop subspace identification algorithm based on correlation function estimates.* Science China Information Sciences *58* (2015), No. 3, 1–10.

[9] C. Poussot-Vassal, O. Sename, L. Dugard: *Vehicle dynamic stability improve-*

ments through gain-scheduled steering and braking control. Vehicle System Dynamics *49* (2011), No. 10, 1597–1621.

[10] L. DoA, O. Sename, L. Dugard: *LPV modeling and control of semi-active dampers in automotive systems*. Control of Linear Parameter Varying Systems with Applications. Springer US, 2012: 381–411.

[11] M. Doumiati, O. Sename, L. Dugard: *Integrated vehicle dynamics control via coordination of active front steering and rear braking*. European Journal of Control *19* (2013), No. 2, 121–143.

[12] D. Ge, X. Huang, H. Gao: *Multi-loop gain-scheduling control of flexible air-breathing hypersonic vehicle*. International Journal of Innovative Computing Information & Control Ijicic *7* (2011), No. 10, 195–208

[13] W. Gai, H. Wang, T. Guo: *Modeling and LPV flight control of the Canard Rotor/Wing Twin Rotor MIMO System*. International Conference on Artificial Intelligence, Management Science and Electronic Commerce. IEEE, (2011), 2187–2191.

[14] L. Ma, Y. Zhang: *DUKF-based GTM UAV fault detection and diagnosis with nonlinear and LPV models*. Mechatronics and Embedded Systems and Applications (MESA), 2010 IEEE/ASME International Conference on. IEEE, (2010), 375–380.

[15] T. Peni, Z. Szabo, B. Vanek: *Model recovery anti-windup compensator design for magnitude and rate saturated LPV systems*. (2013), 4479–4484.

[16] D. Rotondo, F. Nejjari, V. Puig: *Quasi-LPV modeling, identification and control of a twin rotor MIMO system*. Control Engineering Practice *21* 2013, No. 6, 829–846.

[17] D. Rotondo, F. Nejjari, V. Puig: *Model reference quasi-LPV control of a quadrotor UAV*. Control Applications. IEEE, (2014), 736–741

[18] D. Rotondo, A. Cristofaro, T. A. Johansen: *Icing detection in Twin Rotor MIMO Systems with longitudinal motion using an LPV unknown input observer*. IEEE Multi-Conference on Systems and Control. (2015), 984–989.

[19] M. Rodrigues, H. Hamdi, B. H. Braiek: *Observer-based fault tolerant control design for a class of LPV descriptor systems*. Journal of the Franklin Institute *351* (2014), No. 6, 3104–3125.

[20] D. H. Shim, H. J. Kim, H. Chung: *Multi-functional autopilot design and experiments for rotorcraft-based Twin Rotor MIMO Systems*. Digital Avionics Systems, (2001). Dasc. Conference. (2001), 3C4/1–3C4/8 vol. 1, 398–406.

[21] J. W. van Wingerden, M. Verhaegen: *Subspace identification of bilinear and LPV systems for open-and closed-loop data*. Automatica *45* (2009), No. 2, 372–381.

[22] D. Akin, I. B. Kucukdemiral, C. Galip: *L 2 control of LPV systems with saturating actuators: polya approach*. Optimal Control Applications & Methods *34* (2013), No. 1, 17–34.

[23] G. J. Balas: *Flight control law design: an industry perspective*. European Journal of Control *9* (2003), No. 2, 207–226.

Received August 16, 2017