Theory and Applications of Characteristic Modeling: An Introductory Overview
Hong-Xin Wu, Jun Hu, Yongchun Xie, Bin Meng and Zongli Lin

Abstract—Characteristic modeling is a control oriented modeling approach that takes into account both the dynamic characteristics of the plant to be controlled and the performance specifications of the control system. In this article, we give an introductory overview of characteristic modeling. The basic concept, key features, and underlying mechanism are first reviewed. The characteristic modeling based control design and the stability of the closed-loop system are then illustrated. An example of successful applications of the characteristic modeling in control designs is recalled to demonstrate the effectiveness of the design method. Finally, motivations of the characteristic modeling are summarized and future work is proposed.

Keywords: Characteristic model, adaptive control, control designs, control applications, active magnetic bearings

1. INTRODUCTION

Characteristic modeling was initiated by researchers from Beijing Institute of Control Engineering in the 1990s and first published in [23]. It was motivated by the gap that exists between control theory and its engineering applications caused by traditional modeling methods that focus on the dynamic characteristics of the plant. Characteristic modeling takes into account both the dynamic characteristics of the plant to be controlled and the performance specifications of the control system and is thus a control oriented modeling approach. It is different from the traditional modeling whose sole objective is to capture the plant dynamics as precisely as possible, without taking into account the performance specifications of the control system to be designed based on it.

In general, a characteristic model, represented by a slowly time-varying difference equation, should possess the following four key features. First, under a given input, the output of the characteristic model is equivalent to that of the actual plant, in the sense that, their difference stays within a prescribed range during the transient process and approaches zero in the steady state. Second, the order and the explicit form of a characteristic model mainly rely on, apart from plant characteristics, control performance specifications. Third, it is simple, and thus is more convenient for control design and implementation. Fourth, It is different from a reduced-order model. It compresses all the information of a higher order model into several characteristic parameters. In the bandwidth of the control system, no information is lost.

The development of the characteristic modeling method has been motivated by the all-coefficient adaptive control design [20], [24]. Since its initial development, this modeling method has been validated and gradually refined through many engineering projects by the original authors and many other researchers in China [20], [22]. Examples of successful engineering applications are automatic rendezvous and docking of spacecraft Shenzhou-8 and Shenzhou-9 with the orbiter Tiangong-1 [8], [25], adaptive re-entry lifting control of manned spacecraft [6], control of an aluminum electrolysis process [19], adaptive control of spacecraft instantaneous thermal current [7], attitude control of spacecraft with deployable and retractable flexible structures [22], and stabilization of a high speed flexible rotor suspended on active magnetic bearings (AMBs) [4].

Simulation studies have also been performed on the application of characteristic model based adaptive control to several challenging control problems such as the control of near-space hypersonic vehicles [3]. The atmospheric density is versatile in near space, which is at the junction of aerodynamics and astrodynamics, where the effects of control torques are not steady. This adverse flight environment, coupled with the demand for high agility at hypersonic speeds, makes the control of such vehicles very difficult. Control strategies for such vehicles have been developed based on characteristic modeling and validated through simulation on hypersonic vehicles [5], [12].

The objective of this paper is to provide an introductory overview of this emerging modeling approach and its successful applications in control design. In particular, we will first illustrate the basic concept and the mechanism of characteristic modeling of linear plants. Based on the characteristic model of a linear plant, the design of adaptive control laws is then demonstrated. These modeling and control design approaches are then extended to nonlinear systems. An example of successful application in the control of active magnetic bearing systems is reviewed. Finally, as a conclusion to the paper, motivations of the characteristic modeling are summarized and future work is proposed.

2. CHARACTERISTIC MODELING AND ITS MECHANISM

Characteristic models can be roughly divided into two types. One is the definite characteristic models, usually corresponding to plants that are complicated but can be described by mathematic models. The other is the intelligent models, generally for uncertain plants that cannot be represented by
mathematical models. Both characteristic models have been studied and applied in practice. In this paper, we only focus on definite characteristic models. In order to illustrate the mechanism of characteristic modeling, we take two classes of plants as examples, higher order linear systems and nonlinear systems affine in control with a relative degree of 2.

Consider a linear time-invariant plant represented by the following transfer function

$$G(s) = \frac{b_m s^m + b_{m-1} s^{m-1} + \cdots + b_1 s + b_0}{s^n + a_{n-1} s^{n-1} + \cdots + a_1 s + a_0}, \quad (1)$$

where $a_i, i = 0, 1, \cdots, n - 1$, and $b_i, i = 0, 1, \cdots, m$, are constant plant parameters. To illustrate the mechanism of characteristic modeling, we consider a special situation where the plant transfer function (1) can be expressed in the following form by partial fraction expansion [22].

$$G(s) = \frac{k_{v,1}}{s} + \frac{k_{v,2}}{s^2} + \sum_{i=1}^{m} \frac{k_{v,i}}{s + \lambda_i} + \sum_{i=1}^{p} \frac{k_{b,i}}{(s + \omega_i)^2} + \sum_{i=1}^{q} \left( \frac{k_{p+i}}{s + \lambda_{p+i}} + \frac{k_{p+i}}{s + \lambda_{p+i}} \right), \quad (2)$$

where $\lambda_i, i = 1, 2, \cdots, m$, for some integer $m \geq 0$, and $\omega_i, i = 1, 2, \cdots, p$, for some integer $p \geq 0$, are real numbers, $\lambda_{p+i}, i = 1, 2, \cdots, q$, for some integer $q \geq 0$, are complex numbers, and $k_{v,1}, k_{v,2}, k_{a,i}, k_{b,i}$, and $k_{p+i}, i = 1, 2, \cdots, p$, and $k_{p+i}, i = 1, 2, \cdots, q$, are constant real numbers. Here, for a complex number $\alpha$, $\bar{\alpha}$ denotes its complex conjugate.

When $k_{v,1} \neq 0$, a stable closed-loop system will have the ability to track a constant input with zero steady state error, and when $k_{v,2} \neq 0$, a stable closed-loop system will have the ability to track a ramp input with zero steady state error.

The characteristic model of plant (2) for the control objective of tracking a constant or ramp input is a second order time-varying difference equation.

**Theorem 1:** [22] Consider the linear time-invariant plant (2). Let the control objective be tracking a constant or ramp input. Then, for a sufficiently small sampling period, the plant model (2) can be approximated by the following second order time-varying difference equation, referred to as the characteristic model of the plant,

$$y(k) = f_1(k-1)y(k-1) + f_2(k-1)y(k-2) + g_0(k-1)u(k-1) + g_1(k-1)u(k-2), \quad (3)$$

where $y(k)$ and $u(k)$ are respectively the output and input at the $k$th sampling point. Moreover, when the plant is stable, the following properties hold:

- The coefficients of Equation (3) are slowly time-varying.
- The ranges of the values of these coefficients can be determined.
- The output of the plant and that of the characteristic model, in response to a given input signal, are equivalent in the sense that they can be made arbitrarily close to each other by decreasing the sampling period.
- If the plant (2) is stable, that is $k_{v,1} = k_{v,2} = 0$, then the steady state gain of the characteristic model (3) is equal to the DC gain of the plant, and if, in addition, the DC gain of the plant equals 1, then the sum of all coefficients of the characteristic model (3) equals 1 at steady state, that is,

$$f_1(\infty) + f_2(\infty) + g_0(\infty) + g_1(\infty) = 1. \quad (4)$$

The characteristic model establishes that a higher order plant (2) can be equivalently expressed as a second order difference equations, whose slowly time-varying coefficients are unknown, but fall in ranges that can be determined. As a result, the plant (2) can be controlled as a second order system with unknown coefficients by a simple adaptive control law.

The derivation of the characteristic model (3) involves the approximation of each term in the plant model (2) with a second order ordinary difference equation and judiciously combining many such second order ordinary difference equations to result in a single second-order time-varying difference equation with the properties as stated in Theorem 1. Naturally, when the plant model contains terms of orders higher than 2 or the control objective entails the plant to be of Type III or higher types, the characteristic model will be of a higher order.

Characterizing modeling and its applications in control design have been extended to various classes of nonlinear systems [22]. In what follows, we recall the characteristic modeling of a minimum-phase nonlinear system with a relative degree of 2.

Consider the following nonlinear system in the global normal form [9],

$$\begin{align*}
\dot{\eta} &= \zeta(\eta, \xi_1), \\
\dot{\xi}_1 &= \xi_2, \\
\dot{\xi}_2 &= \alpha(\eta, \xi_1, \xi_2) + \beta(\eta, \xi_1, \xi_2)u, \\
y &= \xi_1,
\end{align*} \quad (5)$$

where $\xi_1, \xi_2 \in \mathbb{R}$ and $\eta \in \mathbb{R}^{n-2}$ are the states of the system, $u \in \mathbb{R}$ is the input, $y \in \mathbb{R}$ is the output, and $\zeta : \mathbb{R}^{n-1} \to \mathbb{R}^{n-2}$, $\alpha : \mathbb{R}^n \to \mathbb{R}$ and $\beta : \mathbb{R}^n \to \mathbb{R}$ are functions that are locally Lipschitz in their variables with $\zeta(0,0) = 0$, $\alpha(0,0,0) = 0$ and $\beta(\eta, \xi_1, \xi_2) > 0$ for all $\eta \in \mathbb{R}^{n-2}, \xi_1, \xi_2 \in \mathbb{R}^n$.

Clearly, the nonlinear system (5) is of relative degree 2. We further assume that the system is of strong minimum phase, that is, its zero dynamics

$$\dot{\eta} = \zeta(\eta, 0)$$

is globally exponentially stable at its equilibrium point $\eta = 0$.

The characteristic model of the nonlinear system (5) takes the following form,

$$y(k) = f_1(k-1)y(k-1) + f_2(k-1)y(k-2) + g_0(k-1)u(k-1), \quad (6)$$

where the coefficients $f_1(k), f_2(k)$ and $g_0(k)$ belong to a certain convex closed set that relates to the structure of plant (5). More details on the characteristic modeling of this nonlinear system can be found in [22].

3. Characteristic Model Based Control Design

In this section, we will introduce a control design based on the characteristic model of a linear plant and briefly describe research progress in the stability analysis of the closed-loop system.
3.1. Control Design

As pointed out in Section 2, the ranges of the coefficients $f_1(k), f_2(k), g_0(k)$ and $g_1(k)$ in the characteristic model can be determined [21], [26]. According to all-coefficient adaptive control theory [22], in practice, $g_0(k) \in [0.003, 0.3]$ and $\|g_1(k)\| \leq g_0(k)$. For an unstable plant, if $T/T_{\text{min}} \in [1/10, 1/4]$, where $T_{\text{min}}$ is the minimum equivalent time constant of the plant as defined in [21], then the ranges of $f_1(k)$ and $f_2(k)$ can be determined as

$$
\begin{align*}
 f_1 &\in [1.9844, 2.2663], \\
 f_2 &\in [-1.2840, -1], \\
 f_1 + f_2 &\in [0.9646, 1].
\end{align*}
$$

In the other hand, for a stable plant, if $T/T_{\text{min}} \in [1/10, 1/3]$, then the ranges of $f_1(k)$ and $f_2(k)$ can be determined as

$$
\begin{align*}
 f_1 &\in [1.4331, 1.9975], \\
 f_2 &\in [-1, -0.5134], \\
 f_1 + f_2 &\in [0.9196, 1].
\end{align*}
$$

Thus, in developing the adaptive algorithm for estimating the coefficients of the characteristic model of an unstable plant, we will limit the coefficients $f_1(k)$ and $f_2(k)$ to the following set

$$
N = \{(f_1, f_2, g_0, g_1) : 1.9844 \leq f_1 \leq 2.2663, \\
-1.2840 \leq f_2 \leq -1, \ 0.003 \leq g_0, g_1 \leq 0.3\}.
$$

To facilitate the estimation of its coefficients, we re-write the characteristic model (3) as follows,

$$
y(k) = \phi(k-1)\theta(k-1),
$$

with

$$
\phi(k-1) = \begin{bmatrix}
y(k-1) \\
y(k-2) \\
u(k-1) \\
u(k-2)
\end{bmatrix}, \quad \theta(k-1) = \begin{bmatrix}
f_1(k-1) \\
f_2(k-1) \\
g_0(k-1) \\
g_1(k-1)
\end{bmatrix}.
$$

Let $\hat{\theta}(k) = [\hat{f}_1(k) \ \hat{f}_2(k) \ \hat{g}_0(k) \ \hat{g}_1(k)]^T$ be the estimate of vector $\theta(k)$ which contains the coefficients in the characteristic model. Then, the estimation error $\epsilon(k)$ of the system output is given as

$$
\epsilon(k) = y(k) - \phi(k-1)\hat{\theta}(k-1).
$$

The estimate $\hat{\theta}(k)$ can be updated by the gradient adaptive law along with a parameter projection as follows,

$$
\begin{align*}
\hat{\theta}_u(k) &= \hat{\theta}(k-1) + \frac{\gamma \phi(k-1)\epsilon(k)}{\delta + \phi^T(k-1)\phi(k-1)}, \\
\hat{\theta}(k) &= \pi\left(\hat{\theta}_u(k)\right),
\end{align*}
$$

where $\delta > 0$, $0 < \gamma < 1$, and, for a vector $x \in \mathbb{R}^4$, $\pi(x)$ is the projection of $x$ into the set $N$.

The characteristic model based all-coefficient adaptive control $u_c(k)$ is formulated as,

$$
u_c(k) = u_{c1}(k) + u_{c2}(k) + u_{c3}(k) + u_{c4}(k),
$$

where $u_{c1}(k)$, $u_{c2}(k)$, $u_{c3}(k)$ and $u_{c4}(k)$ are respectively specified as follows:

- Maintaining/tracking control:

\[
u_{c1}(k) = \frac{1}{g_0(k) + \lambda_0} \left(y_r(k+1) - \hat{f}_1(k)y_r(k) - \hat{f}_2(k)y_r(k-1) - \hat{g}_1(k)u_{c1}(k-1)\right),\]

where $y_r(k)$ is the reference system output, $\lambda_0$ is a positive constant, and $\hat{f}_1(k), \hat{f}_2(k), \hat{g}_0(k)$ and $\hat{g}_1(k)$ are the estimates of $f_1(k), f_2(k), g_0(k)$ and $g_1(k)$, respectively.

In practice, we use the following maintaining/tracking control instead,

\[
u_{c1}(k) = \frac{1}{g_0(k) + \lambda_0} \left(y_r(k+1) - \hat{f}_1(k)y_r(k) - \hat{f}_2(k)y_r(k-1) - \hat{g}_1(k)u_{c1}(k-1)\right),\]

- Golden section adaptive control:

\[
u_{c2}(k) = \frac{1}{g_0(k) + \lambda_0} \left(l_{c1}\hat{f}_1(k)\hat{y}(k) + l_{c2}\hat{f}_2(k)\hat{y}(k-1) - \hat{g}_1(k)u_{c2}(k-1)\right),\]

where $\hat{y}(k) = y_r(k) - y(k)$, $l_{c1} = 0.382$ and $l_{c2} = 0.618$.

- Logic differential control:

\[
u_{c3}(k) = d_1 \hat{y}(k) \frac{\hat{y}(k-1) - \hat{y}(k-1)}{T},
\]

where $d_1$ is a positive constant and $L$ is a positive integer.

- Logic integral control:

\[
u_{c4}(k) = d_2 \sum_{i=1}^{k} \hat{y}(i)
\]

$$
u_{c4}(k) = u_{c4}(k-1) + d_2\hat{y}(k),
$$

$$
d_2 = \begin{cases}
  k_{i1} & \text{if } y(k)(y(k) - y(k-1)) \leq 0, \\
  k_{i2} & \text{if } y(k)(y(k) - y(k-1)) > \Delta > 0,
\end{cases}
$$

where $k_{i2} > k_{i1} > 0$ and $\Delta > 0$ are constants.

3.2. Stability Analysis

The stability of the closed-loop system consisting of the characteristic model (3) and the golden section adaptive control law has been established in [22] and [26]. Numerous successful engineering applications have indicated that, if the corresponding characteristic model is stabilized by the golden section adaptive control law, then, with appropriate choice of the sampling period, the closed-loop system consisting of the plant and the golden section adaptive control law is stable.

4. An Example of Engineering Applications

Many successful applications of the characteristic model-based control designs have been reported and several such applications were mentioned in Section 1. In this section, we demonstrate a recent application in the control of a flexible rotor-AMB system test rig, as reported on in [4].

Active magnetic bearings (AMBs) have been an active subject of research for decades and are becoming popular in
practical applications [16]. Despite of their many attractive features, the operation of AMBs requires active feedback control. PID control has been the most widely used control method in industrial AMB systems. Because of their simplicity, PID controllers are easy to implement and can be tuned intuitively. A properly tuned PID controller is able to achieve reasonable control performance. However, for systems with complex dynamics, such as flexible rotor-AMB systems, it is difficult for PID controllers to achieve the required robust performance. In recent years, robust control design methods, such as $\mu$ synthesis, have also been applied in AMB applications [11] [15]. Compared with the PID control design, the $\mu$-synthesis approach is able to better handle the uncertainties in the complex system and achieve reliable performance. However, $\mu$-synthesis requires a relatively accurate characterization of the plant dynamics and uncertainties, which in reality is often difficult to obtain. Furthermore, if the properties of the plant change significantly, the $\mu$ controller designed based on the characterization of the original plant and uncertainties might fail to perform properly.

The use of the characteristic model based all-coefficient adaptive control method to stabilize a flexible rotor-AMB test rig was recently explored [4]. Experimental results demonstrate strong potential for the application of the characteristic model based all-coefficient adaptive control in AMB applications.

4.1. Flexible Rotor-AMB Test Rig

Our flexible rotor-AMB test rig [13] was designed and built as a research platform in the Rotating Machinery and Control (ROMAC) Laboratory at University of Virginia. The purpose of this test rig, as shown in Fig. 1, is to emulate an industrial centrifugal gas compressor and to study control of the rotordynamic instability under supercritical operation. The two radial support AMBs are located at the two ends of the rotor. Disks 1 and 2 on the rotor simulate the blades in a compressor and the two exciter AMBs in the middle and quarter spans of the rotor synthesize various effects on the rotor, such as the cross coupling effect of a seal. When the rotating speed increases, the disks will generate the gyroscopic effect which may cause instability in the rotordynamics.

The rotor is 1.23 m long and weighs around 44.9 kg. Four laminated steel journals are mounted on the shaft for the two radial support AMBs at the non-driven end (NDE) and the driven end (DE) and the two radial exciter AMBs at the middle and quarter spans. The air gaps at all the four AMBs are the same at 10 mils. Only the NDE and DE support AMBs are utilized for control. The two exciter AMBs are used to emulate the operating environment such as the presence of disturbances. A 3.7 kW, electric fan cooled, high speed motor with variable frequency drive (VFD), Colombo RS-90/2, is adopted that is able to run the rotor to 18,000 rpm.

4.2. Modeling and $\mu$-Synthesis Control

The dynamics of the test rig is very complex. Several components are involved in the modeling process. A rotor model is derived based on the finite-element analysis method. The shaft length is divided into 50 stations for the lateral rotordynamic modeling. For the magnetic bearings, a linearized magnetic circuit model is adopted. The sensors, anti-aliasing filters (AAF) and amplifiers are described by their transfer functions. The combined model of the overall test rig has 452 states. Since higher modes beyond the third bending critical frequency contribute negligible effects on the entire system dynamic response, they are truncated and the final reduced order model possesses 36 states with 4 inputs and 4 outputs at the driven end ($x$ axis (DEX) and $y$ axis (DEY)) and the non-driven end ($x$ axis (NDEX) and $y$ axis (NDEY)). This 36th order model serves as the nominal model of the test rig.

A realistic characterization of the uncertainty is essential in the design of a $\mu$-synthesis controller. Two major sources of uncertainties in the test rig are identified. The first one is the gyroscopic effect, which varies with the rotating speed. The main influence of the gyroscopic effect is to split the system eigenvalues into forward and backward modes with different natural frequencies. The other major source of uncertainty is the cross-coupled stiffness (CCS), which depends heavily on the load of the rotor.

Based on the nominal model of the test rig and the uncertainty characterization, a $\mu$-synthesis controller has been designed in [14], [15]. The design utilizes the Matlab function dksyn to carry out four D-K iterations and arrive at a reasonable $\mu$ value. The result is a 48th order controller with $\mu = 0.856$.

4.3. Characteristic Model Based All-coefficient Adaptive Control

In [4], a characteristic model based all-coefficient adaptive control was designed and implemented. The performance of this controller was compared to that of the $\mu$-controller designed and implemented in [14], [15]. In particular, the experimental results, for both the $\mu$-synthesis control and the characteristic model based all-coefficient control, have been recorded for a speed range up to around 14,400 rpm. These
results are recalled in Figs. 2 and 3, in which it can be observed that, for both controllers, the control signals display several peaks when the rotor passes through the rigid body modes and moves towards the first bending mode. In terms of the level of vibration, the characteristic model based all coefficient adaptive controller results in lower levels of vibration at both the driven end and at the non-driven end.

5. SUMMARY AND CONCLUSIONS

Many successful applications indicate a strong potential of the characteristic model based control design method and motivate further theoretical development. More specifically, the motivations for the characteristic modeling can be summarized as follows.

- **Accurate dynamic models are hard to build for complex systems**
  Control design based on a mathematical model of the plant has played an important role in the development and practical applications of control theory. However, with the rapid development of technology, the plants to be controlled are becoming more and more complex. Developing accurate models for such plants are difficult. On the other hand, performance requirements on the control systems are also becoming more and more stringent. Furthermore, simplicity and reliability of a control system are also becoming more desired. Take spacecraft control as an example. A complex spacecraft not only has large flexible attachments and movable parts, but also carries liquid fuel that sloshes and decreases in weight as time goes by. As a result, it is very difficult to model it accurately. However, the requirements on the stability and agility of such spacecraft are usually very high. Unlike the traditional optimal control and adaptive control designs, the characteristic model based control design method circumvents the need of a sophisticated mathematical model of the plant to be controlled. The idea of characteristic modeling reflects the insightful advice of T.S. Tsien [17]: “This is all more true when one realizes that the mathematical difficulties of any subject are usually quite artificial. With a little reinterpretation, the matter could generally be brought down to the level of a research engineer.”

- **The desires for intelligent controllers and low-order controllers**
  In theory, intelligent control does not rely heavily on the precise model of the plant and is capable of achieving high control performance for a complex plant [1]. In reality, most existing intelligent control methods, such as fuzzy control, neural network control, and expert systems, require on-site tuning of the controller structure and parameters. As pointed out in [2], we are still unable to predict what the future of intelligent control theory is like and need to continue our endeavor to explore the basic concepts and theory of intelligent control. Our research and engineering practice lead us to believe that intelligence control relies on an “intelligent modeling theory.” Characteristic modeling has been initiated toward such an intelligent modeling method.

- **Characteristic modeling is a natural development in control theory**
  A review of the history of automatic control technology reveals that, in the plant modeling point of view, there are two distinct approaches to automatic control, the mechanism based approach and the mathematical approach. The mechanism based approach to control design does not rely on the mathematical model of the plant. Instead, it is guided by the idea of feedback mechanism and constructs a controller based on a general understanding of the plant dynamics and the performance specifications. Such a design often resorts to on-line or off-line test to help with the determination of parameter values. Examples of such a control design include PID control designs, fuzzy controls, and neural network based controls. In fact, such a control design approach is reflected in the design of the south pointing carriage in ancient China over two thousand years ago and the Chinese water clock (1086-1089AD) [10].

  The mathematical approach to control design relies on a precise mathematical model to arrive at a controller according to certain control performance specifications. Examples include modern control designs such as time optimal control design. The advantage of such a design approach is the ease of stability and performance analysis its enables. Such a design approach also poses a challenge in its practical application, as many plants, especially those of complex time-varying nature, are difficult to model precisely.

  Summarizing the pros and cons of these two approaches, it is not difficult to conclude that the mechanism based approach does not need to rely on the mathematical model but does not facilitate stability and performance analysis either. On the other hand, the mathematical approach relies on the mathematical model and facilitates stability and performance analysis of the resulting closed-loop system. However, it is often a challenge and even impossible to build a reasonably precise mathematical model of the plant. As a result, it is often hard to apply the mathematical approach in a practical situation. Its numerous successes in practical applications indicate that the characteristic modeling based control design achieves a balance between these two design approaches.

  As a new modeling approach, characteristic modeling entails different modeling methods for different plants. Even for the same plant, the characteristic model may take quite different forms for different control requirements. Further investigation of this new modeling approach, both in theoretical development and in engineering application, is required.

ACKNOWLEDGMENT

This work was supported in part by the National Natural Science Foundation of China (Grant Nos. 60736023, 61273153 and 61333008) and in part by the National Key Basic Research and Development Program of China (Grant No. 2013CB733100).
Fig. 2. Experimental results with the $\mu$-synthesis controller: control signals, shaft displacements and orbit size, at the driven end (left column) and at the non-driven end (right column).

REFERENCES

Fig. 3. Experimental results with the characteristic model based all-coefficient adaptive controller: control signals, shaft displacements and orbit size, at the driven end (left column) and at the non-driven end (right column).

No. 6, pp. 1-5, 2011.


Hongxin Wu, a member of Chinese Academy of Sciences, was born in Jiangsu Province, China, in 1939. He graduated from the Department of Automatic Control, Tsinghua University, in 1965. He is currently a professor, a Ph.D. supervisor, and an advisor of the Science and Technology Committee of Beijing Institute of Control Engineering, the China Academy of Space Technology and the China Aerospace Science and Technology Corporation. His research mainly focuses on the theory and applications of adaptive control and intelligent control in the field of aerospace and other industries. He proposed a novel set of systematic and practical theory and method named “all-coefficient adaptive control.” For a class of plants to be controlled, this method guarantees the stability of the closed-loop systems and good performance even in the transient process when parameter estimates have not converged to their ‘true values.” In Intelligent control, he put forward ‘characteristic modeling,’ ‘golden section adaptive control method,’ etc. These new ideas and methods open new horizons for the design of reduced-order controllers and intelligent controllers, and are of important theoretical significance and practical value for the development of spacecraft control and industrial control. Up to now, the above theory and methods have been successfully applied to many practical plants in spacecraft control and industrial process control. He has published more than 70 papers and authored two monographs. He was honored by a second class and a third class National Award for Inventions, and a first class and five second class Ministerial Award for Science and Technology Progress.

Jun Hu received his B.E. degree in automatic control from Tsinghua University, Beijing, China, in 1986, his M.E. degree in automatic control from the Beijing Institute of Control Engineering (BICE), Beijing, in 1989, and his Ph.D. degree in mechanics from Beijing University, Beijing, in 1993. Since 1993, he has been with BICE, working on the design, simulation, and implementation of a guidance, navigation, and control (GNC) systems of manned spacecraft. He is currently a Professor of BICE. His interests include GNC system design for spacecrafts and adaptive and robust control theories and their applications.

Yongchun Xie received her B.E. degree in electronic engineering from Tsinghua University, Beijing, China, in 1989, and her M.E. and Ph.D. degrees in automatic control from the Chinese Academy of Space Technology (CAST), Beijing, in 1991 and 1994, respectively. Since 1994, she has been with the Beijing Institute of Control Engineering, CAST, where she is currently a professor. From 1998 to 1999, she was with the Institute of Space and Astronautical Science in Japan as a Foreign Researcher of the Center of Excellence. Her current research interests include intelligent and autonomous control of spacecraft, especially autonomous rendezvous and docking of spacecraft. She is the author of more than 30 papers and is the holder of one national invention patent. Professor Xie received a first grade Ministerial Award for Science and Technology Advancement.

Bin Meng received her Ph.D. degree in systems theory from Academy of Mathematics and Systems Sciences, Chinese Academy of Sciences in 2005. From 2005 to 2007 she was a postdoctoral fellow at Beijing Institute of Control Engineering, where she is currently a senior engineer. Her research interests include control of hypersonic flight vehicle, characteristic modeling, adaptive control and intelligent control. Dr. Meng was the recipient of a second grade National Award for Invention.

Zongli Lin is a professor of Electrical and Computer Engineering at University of Virginia. He received his B.S. degree in mathematics and computer science from Xiamen University, Xiamen, China, in 1983, his Master of Engineering degree in automatic control from Beijing Institute of Control Engineering, Chinese Academy of Space Technology, Beijing, China, in 1989, and his Ph.D. degree in electrical and computer engineering from Washington State University, Pullman, Washington, in 1994. His current research interests include nonlinear control, robust control, and control applications. In these areas, he has published 4 books and over 450 papers, about half of which are in archival journals. He was an Associate Editor of IEEE Transactions on Automatic Control (2001-2003), IEEE/ASME Transactions on Mechatronics (2006-2009) and IEEE Control Systems Magazine (2005-2012). He was an elected member of the Board of Governors of the IEEE Control Systems Society (2008-2010). He has served on the operating committees several conferences and will be the program chair of the 2018 American Control Conference. He currently chairs the IEEE Control Systems Society Technical Committee on Nonlinear Systems and Control and serves on the editorial boards of several journals and book series, including Automatica, Systems & Control Letters, Science China Information Sciences, and Springer/Birkhauser book series Control Engineering. He is a Fellow of the IEEE, a Fellow of the IFAC, and a Fellow of AAAS, the American Association for the Advancement of Science.