Parameter Identification of Radio Telescope Servo System Based on Hammerstein-Wiener Model (Postprint)

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Abstract

The large aperture and high observation frequency band requirements of radio telescopes impose higher demands on the control performance of servo systems. To address the nonlinear coupling problems commonly existing in antenna systems, such as dead zone, saturation, and backlash, a nonlinear modeling method for antenna servo systems based on the H-W (Hammerstein-Wiener) model is proposed. A four-step identification procedure is designed to estimate the input nonlinear block, dynamic linear block, and output nonlinear block of the H-W model. Validation using identification data from the Xinjiang Nanshan 26 m radio telescope demonstrates that, compared with traditional linear system models, the H-W model exhibits superior performance in describing the overall dynamic characteristics of the antenna.

Full Text

Preamble

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摘要射电望远镜的大口径与高观测频段需求对伺服系统控制性能提出了更高要求. 针对天线系统中普遍

To address nonlinear coupling problems such as dead zone, saturation

Keywords: telescopes -methods: data analysis -methods: numerical

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1 引言

As radio telescopes evolve toward larger apertures and higher observation frequencies, improving pointing accuracy becomes increasingly challenging, placing more stringent demands on the dynamic response characteristics and control performance of servo systems. However, various nonlinear coupling effects prevalent in antenna system drive chains—including friction, dead zones caused by backlash, and control velocity saturation [1]—severely constrain the performance of traditional linear control strategies. Research on radio telescope dynamics modeling began in the 1990s, with conventional approaches typically involving idealized approximations of the controlled plant to establish linearized models. Cascone et al. [2] achieved a 12th-order transfer function identification for the Galileo telescope through frequency-domain response analysis.

Ranka et al. [3] established a linear model for the GBT (Green Bank Telescope) using observer/Kalman filter identification algorithms and the eigensystem realization algorithm. Zhang et al. [4] constructed a dynamic model for the elevation system of a 25 m radio telescope through mechanism modeling methods, though this approach yields complex models with difficult-to-measure parameters. Hou et al. [5] employed a linear reconstruction method for nonlinear sampled data, combining singular value decomposition with autoregressive neural networks to identify the dynamic model of a hardware-in-the-loop experimental platform for antenna servo systems, but the resulting model lacked sufficient interpretability. Yang et al. [6] combined correlation analysis with the eigensystem realization algorithm to perform parameterized modeling and model reduction for the dynamic characteristics of radio telescope servo systems. Although these studies achieved linear system parameter estimation, they failed to overcome the theoretical limitations of traditional frequency-domain methods in nonlinear system identification. Excessive linearization not only degrades antenna pointing accuracy and exacerbates tracking delays, but also significantly compresses the effective operating bandwidth of the system.

Nonsmooth nonlinear characteristics such as dead zones, saturation, and backlash are ubiquitous in antenna systems, often severely limiting system performance, causing increased tracking errors and oscillations, and even inducing instability [7]. Dual-motor torque bias methods are commonly employed to mitigate the effects of backlash on the system [8]. For wheel-rail telescopes, setting minimum output thresholds can roughly compensate for dead zones induced by static friction between rails and rollers [9]. Reference [10] performed systematic identification of friction in optical telescopes. Reference [11] designed disturbance observers to estimate and compensate for friction, thereby improving system dynamic performance. Therefore, conducting nonlinear system identification for radio telescope antennas represents an effective approach to enhancing model accuracy and control performance, bearing significant practical engineering value. The Hammerstein-Wiener (H-W) model [12] serves as an important nonlinear system identification methodology and has found applications across numerous fields, including nonlinear compensation for high-power amplifiers in communication systems [13], nonsmooth nonlinear modeling for precision motion platforms [14], and identification and predictive control of industrial chemical processes [15]. The H-W model comprises a cascade of an input static nonlinear module, an intermediate dynamic linear module, and an output static nonlinear module, capable of adequately approximating many practical nonlinear systems. Compared to fully black-box models such as neural networks, its modular design supports the independent identification and optimization of physically observable nonlinearities such as input saturation and output backlash dead zones, retaining a degree of physical interpretability [16]. However, effectively identifying the parameters of each module within the H-W model, particularly when facing complex characteristics in practical systems, remains challenging and requires the development of targeted identification strategies.

To address the modeling challenges arising from multiple coupled nonlinearities (input saturation, friction, and backlash dead zones) in radio telescope servo systems, this paper proposes a modular identification architecture based on the H-W model, enabling the effective separation and identification of key physical nonlinearities such as input saturation and output dead zones. Validation using measured data from the Nanshan 26 m radio telescope demonstrates that the proposed H-W model-based identification method exhibits significant advantages over traditional linear models in both fitting accuracy and nonlinear characteristic description, providing a more precise foundation for the design of subsequent high-performance controllers.

2.1 伺服系统结构

The wheel-rail antenna employs independent control systems for azimuth and elevation degrees of freedom, effectively avoiding mutual interference between the two and ensuring high-precision observation capability under all-weather conditions. The block diagram of the conventional control and transmission structure is shown in [Figure 1: see original paper]. Both azimuth and elevation angle controls adopt a typical three-loop control structure. The

2.2 控制器输入的非线性

To ensure the safety of large structures and prevent motor speeds from exceeding their rated values, the controller output is subjected to speed limiting. To avoid motion oscillation and gear tooth impact in the reducer caused by excessive fluctuations in driving force, the rate of change of the controller output speed is also restricted. Meanwhile, the motor acceleration is limited within the maximum current range of the motor and driver; the servo driver applies ramp processing to the speed loop command input and limits the output current command. These limiting measures are simultaneously applied to the antenna' s azimuth and elevation position controllers, resulting in nonlinear characteristics of the controller output. As a controller widely used in current telescopes, the PID (Proportional Integral Derivative) controller employs anti-windup processing to reduce the effects of integral saturation caused by limiting, which further increases the nonlinearity of the controller. The processing logic of an incremental PID controller for a certain type of telescope is shown in [Figure 2: see original paper], where $e(k)$ is the error, $\Delta u(k)$ is the control increment, $u(k)$ is the total control quantity, and k is the discrete time sampling sequence point. After acceleration and speed limiting, the control quantity exhibits overall saturation nonlinearity as shown below:

The nonlinear characteristics are shown in [Figure 3: see original paper], where the nonlinear function $f_{NL}(\cdot)$ represents the input signal, c_1 is the gain coefficient, $\bar{u}$ is the upper limit value, and $\underline{u}$ is the lower limit value. In the motion stage, the saturation width is determined by $\bar{u}$ and $\underline{u}$ in the equation. Although the saturation module is static, its parameters $\bar{u}$ and $\underline{u}$ may change slowly with displacement. In precision tracking control, if this phenomenon is ignored, it will significantly limit tracking performance and may even lead to actuator failure.

$$f_{NL}(u) = \begin{cases} \bar{u} & c_1 u(k) > \bar{u} \\ c_1 u(k) & \underline{u} \le c_1 u(k) \le \bar{u} \\ \underline{u} & c_1 u(k) < \underline{u} \end{cases}$$

Figure 1 Block diagram of radio telescope antenna control and drive structure

2.3 传动链的动态线性

The antenna drive system of radio telescopes typically employs drivers to control DC or AC motors for speed regulation. During antenna movement, the nonlinear effects produced by the motor are relatively weak and can therefore be neglected; the system approximately exhibits dynamic linear characteristics. The overall motor-driven antenna structure exhibits large-inertia lag characteristics, requiring determination of the system delay period. After selecting appropriate motors and drivers and adjusting control parameters, the equivalent relationship among the driver, motor, and mechanism can be approximated as a discrete-time linear transfer function, whose common form can be written as:

where the gain coefficient is denoted appropriately. The system' s input and output polynomials are represented with weights for each term in the input polynomial and weights for each term in the output polynomial, while z^{-1} denotes the unit delay operator. Figure 2 shows the processing logic block diagram of the incremental PID controller for the telescope, as expressed in Equation (3).

In the equation, the functions are strictly monotonically increasing and decreasing functions, with the input signal and the output at the previous sampling instant. [Figure 4: see original paper] illustrates the nonlinear transmission characteristics of typical backlash, where the output depends not only on the current input but also on previous inputs. The curves are continuous and strictly monotonic for both the increasing and decreasing functions, and therefore possess invertibility. The functions lie on opposite sides with no intersection between them, and each has known horizontal axis intercepts. When the input varies within a certain small range (before the gear gap is "engaged"), the output shows almost no response, resulting in a so-called "dead zone." Taking motor drive as an example, the effects of torque transmission and rotational inertia cause the speeds of the input and output shafts not to change abruptly simultaneously. For convenience in engineering identification and control design, this is often approximated as a dead zone model in the small-amplitude reversal interval. [Figure 5: see original paper] illustrates this equivalent dead zone characteristic. Only when the input exceeds a threshold will force or displacement continue to be transmitted. This dead zone causes the system to be insensitive to small-amplitude changes, thereby resulting in lag, chattering, or other adverse effects in the control system or transmission system.

3.1 模型结构

To characterize static nonlinearities while preserving linear dynamic characteristics, this paper adopts the H-W model for structured modeling of the system.

[Figure 3: see original paper] Saturation nonlinear characteristic diagram.

2.4 齿隙、摩擦产生的输出非线性

Backlash is ubiquitous in mechanical transmission systems, and is particularly unavoidable in scenarios requiring frequent changes in motion direction. It causes system instability during low-speed operation and introduces errors and jumps during direction reversal, thereby severely degrading tracking performance and positioning accuracy. Furthermore, backlash exhibits strong nonlinearity, is analytically intractable, and possesses non-differentiable characteristics. Under conditions of unknown load disturbances and friction, stability issues such as limit cycle oscillations may also arise. Gear backlash is the primary factor generating backlash; when backlash exists, the input and output do not correspond linearly, but rather exhibit a "looseness" phenomenon during reverse meshing or direction switching. Its dynamic characteristics can be described by a nonlinear function $G(z)$ with memory properties:

$$G(z) = \frac{B(z)}{A(z)} = \frac{b_0 + b_1 z^{-1} + \cdots + b_{mz}^{-m}}{1 + a_1 z^{-1} + \cdots + a_{nz}^{-n}}$$

where $B(z)$ and $A(z)$ are polynomials in z^{-1} with coefficients $b_0, \dots, b_m$ and $a_1, \dots, a_n$ respectively. The nonlinear function $n_{NL}(\cdot)$ is defined as:

$$n_{NL}(w) = \begin{cases} g_2[w(k)]; & w(k) > g_{12}[y(k-1)] \\ y(k-1); & g_{11}[y(k-1)] \le w(k) \le g_{12}[y(k-1)] \\ g_1[w(k)]; & w(k) < g_{11}[y(k-1)] \end{cases}$$

where g_1 and g_2 are functions of $w(k)$ and $y(k-1)$, with $g_2(\cdot)$ and $g_1(\cdot)$ representing the upper and lower envelope functions respectively. The Hammerstein-Wiener model consists of an input-side static nonlinearity, a dynamic linear module, and an output-side static nonlinearity connected in series, as shown in [Figure 6: see original paper]. The output of the input-side static nonlinearity $f_{NL}(\cdot)$, denoted $v(k)$, serves as the input to the dynamic linear module $G(z)$; the output of the linear module, denoted $w(k)$, serves as the input to the output-side static nonlinearity $n_{NL}(\cdot)$, with the final output $y(k)$ representing the antenna angular response. The intermediate variable $w(k)$ is consistent with the notation in Section 2.

[Figure 4: see original paper] Nonlinear characteristics of conventional backlash

[Figure 5: see original paper] Dead zone characteristics of the backlash

[Figure 6: see original paper] Schematic structure of the H-W nonlinear model

Correspondingly, this structure can be expressed as:

$$\begin{cases} v(k) = f_{NL}[u(k)] \\ w(k) = G(z)v(k) \\ y(k) = n_{NL}[w(k)] \end{cases}$$

where $u(k)$ is the system input, $v(k)$ is the output of the input-side nonlinear module, $w(k)$ is the output of the linear module, and $y(k)$ is the system output.

Traditional backlash models contain dynamic memory components and therefore do not satisfy the static nonlinearity requirements of the H-W model' s nonlinear modules. In practical engineering, to suppress the hysteresis nonlinearity caused by backlash and achieve rigid disturbance rejection, electrical anti-backlash methods are commonly employed by injecting equal-amplitude opposite-direction speed or current bias into dual motors. The bias torque must be sufficiently large to overcome friction and eliminate the gap, yet not so large as to severely constrain position control performance. However, speed or current bias also introduces additional nonlinearities into the drive chain, and electrical anti-backlash cannot completely eliminate backlash nonlinearity. Therefore, to satisfy the static characteristic requirements of the H-W model, a dead-zone model is adopted to provide a simplified description of the backlash nonlinearity, expressed as:

$$n_{NL}(w) = \begin{cases} c_2[w(k)-\delta]; & w(k) > \delta \\ 0; & -\delta \le w(k) \le \delta \\ c_3[w(k)+\delta]; & w(k) < -\delta \end{cases}$$

The above equation defines a parameterized dead-zone nonlinear module. When the input exceeds the upper threshold δ, the output is linearly amplified by gain c_2; when the input falls below the lower threshold $-\delta$, the output is linearly attenuated by gain c_3; within the dead-zone interval between $-\delta$ and δ, the output remains zero. This model is a static scalar piecewise linear nonlinear function. However, due to its non-smoothness (non-differentiability at threshold points), numerical computation difficulties may arise. To ensure the invertibility assumption of the nonlinear module output holds, piecewise polynomial interpolation can be employed to smooth the inverse mapping near the threshold points.

The triple-structure H-W system model universally faces the problem of parameterization uniqueness, meaning that the model identification results form a set rather than a fixed value. To address this issue, the following analysis and assumptions are made: in the description of the saturation nonlinear module, the input $u(k)$ is a non-decreasing function with non-negative slope, while the dynamic linear module $G(z)$ contains integral action. Therefore, after the two modules are connected in series, the relationship between the input and intermediate variables is: the gains of the saturation and dead-zone nonlinear modules can be unified into the dynamic linear module. By setting the gains of $f_{NL}(\cdot)$, $n_{NL}(\cdot)$, and $G(z)$ all to unity, unified modeling and identification are achieved through the gain of the dynamic linear module. Ultimately, the H-W model is fully parameterized, yielding the following descriptive equations.

The H-W system model parameters to be identified are:

3.3 辨识误差来源分析

In practical applications, the identification accuracy of this method may be affected by various factors. To minimize the impact of these errors, it is essential to design experiments properly, select appropriate model structures, employ robust identification algorithms, and conduct thorough model validation. The primary sources of error can be summarized as follows:

1. Measurement noise in experimental data: quantization errors, sampling effects, or additional noise may be introduced during the

3.2 辨识流程

A four-step identification procedure is designed for the Hammerstein-Wiener (H-W) model parameters: 1. Dynamic linear module identification: conventional transfer function or subspace identification methods can be employed to obtain the structural parameters of the module; 2. Input nonlinearity estimation:

Using the preliminary identification results, the intermediate variable dataset is constructed, and the input nonlinear module is estimated to obtain $\hat{f}_{NL}$; 3. Output nonlinearity estimation: using $\hat{f}_{NL}$, the intermediate variable dataset is estimated, and the output nonlinear module is estimated using the intermediate variable and output datasets to obtain $\hat{n}_{NL}$; 4. Iterative optimization: the iteration proceeds with the objective of minimizing the output error. To validate the effectiveness of the proposed identification method, experimental validation was conducted using measured data from the azimuth servo system of the 26 m radio telescope at the Nanshan station of the Xinjiang Astronomical Observatory. In the experiment, the position closed-loop control loop of the servo system was disconnected, the velocity command was used as the excitation input, and the axis angle encoder feedback signal was collected as the output response. The structural block diagram of the experimental system is shown in [Figure 7: see original paper]. According to the literature [6], the main resonance peak of the servo system is located near 2 Hz, and the data sampling rate is 20 Hz (corresponding to a control period of 0.05 s). To excite the high-frequency characteristics of the antenna, a sinusoidal sweep signal in the [0, 5] Hz range was selected as the velocity excitation. The choice of 5 Hz as the upper frequency limit was primarily based on the consideration that this range already covers the antenna servo control bandwidth, while in higher frequency ranges (e.g., [5, 10] Hz), the influence of measurement noise and other high-frequency disturbances in the output signal becomes relatively more significant, resulting in a lower signal-to-noise ratio that is unfavorable for accurate system identification.

The H-W model parameters obtained through identification are as follows: the final identified model parameters yield $v(k)/u(k)$; $w(k)/\sum v(k)$; $w(k)/\sum u(k)$; (6) $G(z)c_1c_2c_3(\cdots)y(k) = n_{NL}fG(z)f_{NL}[u(k)]g$; (7) $B' = \begin{pmatrix} b_0 \\ b_1 \\ \vdots \\ b_m \end{pmatrix} = \begin{pmatrix} b'_0 \\ b'_1 \\ \vdots \\ b'_m \end{pmatrix}$; (8) $\tilde{A} = \begin{pmatrix} a_1 \\ a_2 \\ \vdots \\ a_n \end{pmatrix}, \tilde{B} = \begin{pmatrix} b'_0 \\ b'_1 \\ \vdots \\ b'_m \end{pmatrix}, \tilde{C} = \begin{pmatrix} \alpha \\ \beta \end{pmatrix}, \tilde{D} = \begin{pmatrix} \gamma \\ \delta \end{pmatrix}$; (9) $\{l := n+m; u(k) = 0; y(k) = 0; \text{when } k \leqslant 0\}$; (10) $f_{NL}(u) = \begin{cases} 0.438, & u(k) > 0.438 \\ u(k), & -0.335 \leqslant u(k) \leqslant 0.438 \\ -0.335, & u(k) < -0.335 \end{cases}$; (11) $G(z) = \frac{0.004828z^{-3}-0.01261z^{-4}+0.0159z^{-5}-0.009702z^{-6}-0.003579z^{-7}+0.01059z^{-8}-0.009064z^{-9}+0.003634z^{-10}}{1-3.726z^{-1}+6.032z^{-2}-4.712z^{-3}-0.486z^{-4}+5.157z^{-5}-5.586z^{-6}+3.056z^{-7}-0.6973z^{-8}-0.03809z^{-9}}$; (12) The corresponding model identification results are shown in [Figure 8:

see original paper], where the blue solid line represents the actual system response curve, and the red dotted line represents the response curve of the identified H-W model. It can be observed from the figure that the H-W model can accurately approximate the motion characteristics of the antenna azimuth servo system.

Figure 7 Block diagram of azimuth servo identification for Nanshan 26 m radio telescope. Where y is the actual value, $\hat{y}$ is the predicted value, $\bar{y}$ is the mean of the actual values, and N is the total number of data points.

Figure 8 Comparison between the actual response of the system and the identification results. To compare with the linear model, the subspace identification method was used to identify the same dataset, and a linear identification model was obtained. Two additional sets of excitation-response data were used for validation.

结果如图 9 所示：蓝色实线为采样获得的实际系统

response, the red dotted line represents the H-W identification model response, and the green dashed line represents the linear identification model response. The goodness of fit (Fit Percentage) is used to quantify the model accuracy, calculated as shown in equation (14).

Figure 9: Comparison of identification results between linear model and H-W model [Figure 9: see original paper]

From Figure 9, it can be seen that the model identification results proposed in this paper better describe the overall dynamic characteristics of the antenna compared to the linear model obtained by subspace method identification. The proposed model better represents the nonlinear characteristics under weak excitation and more accurately reflects high-frequency characteristics compared to the linear model. For the same set of excitation signals, the H-W model achieves a fit of 94.6% for the actual system response, while the linear model only achieves 86.2%. To further improve identification accuracy, especially for nonlinear characteristics, special excitation signals can be designed, such as amplitude-modulated and phase-modulated sinusoidal sweep signals. By applying excitation signals with smaller amplitudes, the nonlinear characteristics of the system can be more clearly excited, avoiding interference from the linear behavior of the system, thereby more accurately identifying the nonlinear part of the system.

5 结论

This paper addresses the nonlinear coupling problem prevalent in radio telescope servo systems and proposes a nonlinear system identification method based on the Hammerstein-Wiener (H-W) model. Through a designed four-step identification procedure, the input nonlinearity, dynamic linearity, and output nonlinearity modules of the model were successfully estimated. The proposed method was validated using measured identification data from the azimuth axis of the Xinjiang Nanshan 26 m radio telescope. The results demonstrate that, compared to traditional linear models, the H-W model-based identification method proposed in this paper can more accurately describe the overall dynamic characteristics of the antenna servo system, particularly excelling in capturing nonlinear behaviors under weak excitation and high-frequency characteristics. The goodness of fit on the validation dataset reached 94.6%, significantly higher than the 86.2% achieved by the linear model. The modular structure of the H-W model allows for decomposing complex nonlinear systems into relatively independent static nonlinear components and dynamic linear components. This not only facilitates understanding and separating key physical nonlinear effects such as input saturation and output dead zones (simplified backlash), but also enables targeted model optimization and controller design in subsequent work, thereby reducing the complexity of identification and application, and demonstrating good practical engineering value. In the future, we will extend this identification method to the elevation servo system for detailed modeling analysis and performance verification, and based on accurate H-W models of both the azimuth and elevation axes, explore more advanced nonlinear control strategies to further improve the pointing accuracy and dynamic response performance of large radio telescopes.

References Gawronski W. ITCST, 2007, 15: 276 Cascone E, Mancini D, Schipani P. SPIE, 1997: 343 Ranka T, Garcia-Sanz M, Weadon T, et al. 2014 American Control Conference. Portland: IEEE, 2014: 3692 Zhang J Y, Bao H. Electronic Mechanical Engineering, 2018, 34: 50 Hou X Z, Xu Q, Li L, et al. Acta Astronomica Sinica, 2022, 63: 58 Yang L, Liu Z Y, Wang N, et al. Journal of Xinjiang University (Natural Science Edition), 2022, 39:

Nordin M, Gutman P O. Autom, 2002, 38: 1633 Feng J P, Ma W L, Huang J L. Opto-Electronic Engineering, 2009, 36: 64 Brandt J, Ford J, Hunter T, et al. PTCS Project Note

55. Precision Telescope Control System, 2007: 3

Kumar T S, Bastin C, Kumar B. Conference on Ground-Based and Airborne Telescopes VI. Edinburgh:

SPIE, 2016: 99063 Su Y R, Wang Q, Yan F B, et al. RAA, 2021, 21: 185 Wang D Q, Ding F. ISPL, 2012, 19: 825 Sano A, Sun L. Proceedings of the 41st SICE Annual Conference. Osaka: IEEE, 2002, 3: 1521 Zhang Z, Zhang D, Zheng H, et al. 2019 Chinese Control Conference. Guangzhou: IEEE, 2019: 1637 Luo X S, Song Y D. Information Sciences, 2018, 422:

Taringou F, Hammi O, Srinivasan B, et al. IET Circuits Devices & Systems, 2010, 4: 282

Hammerstein-Wiener Model-Based Parameter Identification for Radio Telescope Servo Systems

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Abstract

The large aperture and high observation frequency requirements of radio telescopes impose stringent demands on servo system control performance. To address common nonlinear coupling issues in antenna systems, such as dead zones, saturation, and backlash, this paper proposes an H-W (Hammerstein-Wiener) model-based nonlinear modeling method for antenna servo systems. A four-step identification process is designed to estimate the input nonlinear module, dynamic linear module, and output nonlinear module of the H-W model. Validation using identification data from the 26 m radio telescope in Nanshan, Xinjiang, demonstrates that the H-W model outperforms traditional linear system models in describing the overall dynamic characteristics of the antenna.

Key words telescopes, methods: data analysis, methods: numerical