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Unveiling the Significance and Importance of Parameter Estimation in Nonlinear Biological Control Systems

Arnab Das[1*], Bipa Datta[2] ,Achintya Das[3] And Kabita Purkait[4]

[1] Department of Electronics & Communication Engineering (E.C.E.), Brainware University, Barasat, Kolkata -125, West Bengal, India. (u.call.me.arnab@gmail.com) ORCID 0000-0002-9976-7011

[1, 2] Department of E.C.E., Maulana Abul Kalam Azad University of Technology, West Bengal, India.

[3, 4] Department of E.C.E., Kalyani Government Engineering College, Kalyani, Nadia - 741235, West Bengal, India.

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Abstract:

Every system naturally has nonlinear dynamics. We classify nonlinearity based on whether it's inherent or intentionally added. Inherent nonlinearity which is unavoidable, appears as dead zones, saturation, and friction. Intentional nonlinearity purposely added, alters system performance. Accurate system parameter estimation is crucial for modeling and control design. It allows us to develop models that closely mimic actual system behavior and design control strategies. Initial conditions, system dynamics, and input and output data are vital in identifying system parameters. The accuracy of identified models relies on high-quality data and an understanding of system dynamics. The proposed survey aims to highlight the importance of parameter estimation in nonlinear biological control systems. It introduces a symbolic method to characterize system inputs. Nonlinear observability and extended Lie theory are used to analyze and determine structural identifiability. A suitable methodology integrates these methods to assess structural identifiability. It involves deriving mathematical expressions and designing input profiles to enhance identifiability. MATLAB and SIMULINK are used for simulation and analysis.

Keywords: Nonlinear biological control systems, Adaptation law, Online Parameter estimation, Online Parameter identification.

Introduction

To approximate the behavior of a nonlinear system, we often turn to linearized system approaches. These models are handy for analyzing system behavior under small perturbations around a nominal operating point. However, real-world systems frequently exhibit nonlinear behavior due to changes in parameters, external disturbances, or inherent nonlinear dynamics. Nonlinear biological control systems are systems in which the relationship between the input and output is not a simple linear function. These systems are prevalent in biological organisms due to the complex interactions and feedback mechanisms involved in maintaining homeostasis and adapting to changing environments. Nonlinear phenomena like bifurcations, chaos, and hysteresis are common in such systems, beyond the scope of linear models. Therefore, nonlinear models are essential to fully understanding and analyzing system behavior. Unlike linear models, which can often be described by linear ordinary differential equations (ODE), nonlinear models may involve nonlinear equations, differential or difference equations, or even partial differential equations. Analyzing these models typically requires numerical methods such as simulation or approximation techniques. Yet, the benefits of nonlinear models include better understanding and prediction of system behavior, improved control strategies, and optimization of performance.

Linear systems, described by linear ODEs, often yield solutions expressed as linear combinations of exponential or trigonometric functions. Analyzing linear systems is facilitated by techniques like Laplace transforms, transfer functions, and eigenvalue analysis. Linear systems possess advantageous properties like superposition and homogeneity, making them easier to analyze and control. However, linear models may not capture the full range of system behavior under nonlinear conditions or large perturbations from the nominal operating point. Although mathematical tools like Laplace and z-transforms aid in linear system analysis, no such tools exist for the wide variety of nonlinear systems and phenomena. Thus, qualitative analysis plays a crucial role in predicting system behavior in the absence of closed-form solutions.

Parameter estimation is vital in the measurement, diagnosis, and modeling of nonlinear systems (Astrom, J. K., et al., 2014). State space modeling is crucial in various fields, including control engineering, system identification, and machine learning. However, identifying state space models can be challenging due to unknown noise terms and state variables. An online adaptive estimation algorithm can estimate unknown parameters of dynamic or real-time systems by collecting information from system inputs and outputs. Therefore, identifying and synthesizing unknown nonlinearities can enhance the dynamic or real-time performance of plants or systems (Friedland, B., 2016).

1. Advancements and Challenges in Parameter Estimation for Nonlinear Biological Control Systems

Control systems are generally nonlinear, and nonlinearity may stem from system parameter variations over time. System parameter identification is crucial for achieving the desired response. Optimal experiment design (OED) is a classical technique used in parameter identification, system identification, and control engineering. It involves designing experiments to collect data efficiently for estimating model parameters or identifying system dynamics. OED aims to obtain valuable information for reliable parameter identification by carefully selecting inputs and corresponding measurements. This approach streamlines parameter estimation using advanced statistical and optimization techniques, optimizing data collection while minimizing effort, time, or cost. However, parameter identification and optimal input design are separate from parameter estimation (Ljung, L., 1999). Nonlinear systems with multiple variables can be effectively studied using tools like online parameter estimation and coupled closed-loop optimal experiment design. These tools maximize information from experiments and enhance parameter estimation accuracy, considering the system's non-linearity and multi-variable nature. The Fisher information matrix (FIM) is fundamental in online parameter estimation and coupled closed-loop optimal experiment design approaches. It quantifies the information content of data for estimating unknown parameters, especially in nonlinear multivariable systems. By continuously updating estimates based on measurements, the Kalman filter accurately represents system behavior at steady-state conditions. Model Predictive Control (MPC) or Receding Horizon Control (RHC) is common in control systems, where control inputs are computed by solving optimization problems over finite time horizons. MPC depends on managing computational complexity, real-time constraints, accurate modeling, dynamic environments, and economic objectives alongside system constraints for feasibility. Economic Model Predictive Control (EMPC) incorporates economic considerations into control optimization, minimizing costs while satisfying constraints. The extended Kalman filter (EKF) and parameter adaptive extended Kalman filter (PAEKF) handle nonlinear systems by linearizing dynamics and estimating system states and parameters (Liu, Z., et al., 2015) (Nagy, K. Z., et al., 2007). Differential geometry, heuristic black-box control, and hybrid dynamical systems provide tools for understanding and controlling complex and nonlinear systems (Friedland, B., 2016). An Additional Actuating

Signal (AAS) can enhance control over the system's output in its working environment by improving the normal actuating signal (Datta, B., et al., 2022). The Additional Actuating Signal (AAS) is an extra signal added to a control system alongside the primary actuating signal. Adaptive control with a parameter estimator enhances system performance by continuously updating model parameters, even with unknown and time-varying parameters (Imran, H. I., et al., 2020). Adaptive control focuses on developing systems that adapt to changing dynamics, optimize performance, and achieve stable control in various situations (Zhu, Y., et al., 2011; Netto, M., et al., 2006). Changes in adaptation gain influence the adaptation mechanisms and affect the results, especially in Model Reference Adaptive Control (MRAC) strategies, as seen through the lens of parameter estimation (Das, A., et. al., 2021; Das, A., et. al., 2022).

In real-time systems, proper identification of model parameters is essential for stable and optimal performance. Several mathematical and computer-based models exist for parameter estimation in nonlinear biological control systems. However, a gap remains between theoretical advancements and practical applications.

2. Discussion

Simple examples can demonstrate the significance of adaptive control in parameter estimation. After examining the characteristics of the plant or system and taking into account performance needs, we can suggest employing adaptive control.

Scalar plant with an unknown parameter: Consider a scalar plant or system as

$$\dot{x} = ax + u \qquad (1)$$

where u, x, and a, define the control input, the scalar state of the system, and one unknown parameter, respectively. In any system, we expect the state variable x to remain bounded and approach zero over time. This can be achieved by making a suitable choice of the plant input, u.

Let, the linear control law as

$$u = -kx \qquad (2)$$

where, $k > |a|$, which can fulfill the control objective by considering a known parameter a. Though it can also meet the control objective for the known upper bound as $\underline{a} \geq |a|$, and the specified linear control law with $k > \underline{a}$,

i.e. the closed-loop system or plant will be unstable for $a > k > 0$. In conclusion, the plant can achieve stabilization through a linear controller when the known upper bound of the plant parameter ensures that the state variable x converges to zero over time. To stabilize the plant, it is necessary to use a linear controller with $k > |a|$. Otherwise, online parameter estimators coupled with switching designs are recommended.

The adaptive control law we can establish or represent as

$$u = -kx \qquad (3a)$$

$$\dot{k} = x^2, \qquad (3b)$$

The value of the unknown parameter a is not crucial, but it does ensure that all signals within the system or plant remain bounded, and the state variable x converges to zero.

Parameter estimation and adaptation in adaptive control entail continuously updating model parameters using real-time measurements to enhance the controller's performance and adjust to evolving system dynamics. Therefore, when linear controllers struggle to manage parametric uncertainty effectively, an adaptive control approach emerges as a suitable alternative.

Scalar plant with an unknown parameter and an external bounded disturbance: By considering the same example with a bounded external disturbance d, it can be defined that adaptive control law properties may be more effective than the traditional linear schemes:

$$\dot{x} = ax + u + d, \qquad (4)$$

The unknown disturbance, d can be approximated as

$$d = \sum_{i=1}^{N} \theta_i^* \phi_i(t, x), \qquad (5)$$

where, θ_i^* are unknown constant parameters and $\phi_i(t, x)$ are known functions. For considering the linear control law

$$u = -kx \;, \qquad (6)$$

by, $k > \underline{a} \geq |a|$, we can construct that x is bounded at a steady-state as

$$|x| \leq \frac{d_0}{k-a}, \qquad (7)$$

where d_0 defined as an upper bound for $|d|$.

To meet our requirement, we can achieve a decrease in the steady-state value of x by increasing the controller gain k, as indicated in our approximation (Ioannou, P., et al. 2007). However, using a high-gain controller is undesirable when dealing with high-frequency unmodified dynamics. Additionally, for a nonlinear system with any finite control gain, there is no guarantee that the steady-state value of x will converge to zero over time, as discussed in reference (Ioannou, P., et al. 2007).

It can be guaranteed by using the following adaptive control law by online estimation and canceling the effect of uncertainty via the closed-loop feedback process:

$$u = -kx - \hat{d} \qquad (8a)$$

$$\hat{d} = \sum_{i=1}^{N} \theta_i^* \phi_i(t, x) \qquad (8b)$$

$$\dot{\theta}_i = x \phi_i(t, x) \qquad (8c)$$

where, the controller gains $k > \underline{a} \geq |a|$, for simplicity assuming that $\underline{a}$ is known; else estimation of k is also required.

Adaptive control techniques are highly valuable for improving the performance of nonlinear systems in various conditions, and overcoming the limitations of linear control methods (Ioannou, P., et al. 2007). Nonlinear systems often exhibit complex behaviors beyond the capabilities of linear models, and their performance can vary under different operational conditions.

However, it's essential to recognize that adaptive control may only sometimes be the optimal choice for parameter estimation in every control problem. In some cases, continuous learning processes can gather valuable information about unknown parameters or utilize it for parameter estimation.

Adaptive control algorithms analyze transient response data obtained by exciting the plant or system, extracting valuable information about its dynamics, parameter values, and other characteristics (Ioannou, P., et al. 2007). This information is then used for parameter estimation or adaptation, allowing the adaptive control system to update and adjust its parameters to achieve performance objectives continuously.

However, when sufficient information about system parameters is readily available, linear, robust control techniques may be more suitable than online learning (Liu, Z., et al. 2015). Robust adaptive control techniques are designed to handle uncertainties and disturbances in system dynamics, ensuring stable and effective control even in changing and uncertain operating conditions. The primary goal of robust adaptive control is to develop control systems capable of delivering stable and robust performance without requiring precise knowledge of the system dynamics.

3. Conclusions

The future demands complex systems, presenting both a critical need and an exciting challenge to maintain the desired response. This has sparked increasing interest in the research field of nonlinear biological control systems, which find applications in diverse domains such as energy, robotics, healthcare, biology, and big data analysis. This interest drives the rapid development of advanced theories and innovations.

Designing controllers capable of handling uncertainty and unknown system parameters is crucial, especially for nonlinear systems. This involves addressing modeling errors, parameter uncertainties, and external disturbances. To determine the most appropriate control approach and parameter estimation techniques in such cases, conducting a comprehensive analysis of the system dynamics and uncertainties is essential.

The state space model offers a powerful and versatile framework for designing, analyzing, and optimizing control systems. Its capabilities include capturing the complete system dynamics, managing multivariable and time-varying systems, and facilitating model-based control design. Consequently, it is found to be widespread in control engineering. The state space model provides a mathematical representation of the system dynamics, enabling the design and implementation of advanced control techniques like optimal control, adaptive control, and robust control. These techniques utilize the state space model to incorporate uncertainties, estimate unknown parameters, and optimize control actions to achieve the desired system performance.

Adaptive control can attain or sustain the desired system response level by employing specific techniques. These systematic approaches enable the automatic adjustment of system controllers in real-time or following the reference signal. Designing a disturbance-free plant model using an adaptive scheme is an effective technique when dealing with a time-varying dynamic system or a real-time plant model with unknown parameters.

Parameter estimation is crucial in biological systems to ensure model accuracy, understand underlying mechanisms, and inform personalized medicine by optimizing drug dosing. It aids in designing effective control strategies and interventions in public health and reveals system robustness and stability. Additionally, it is essential in experimental design and interdisciplinary applications like synthetic and systems biology for constructing new biological circuits.

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