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Tracking control of nonlinear lumped mechanical continuous-time systems: A model-based iterative learning approach

K. Smolders, M. Volckaert, J. Swevers*

Department of Mechanical Engineering, Division PMA, Katholieke Universiteit Leuven, Celestijnenlaan 300B, B–3001 Heverlee, Belgium

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Abstract

This paper presents a nonlinear model-based iterative learning control procedure to achieve accurate tracking control for nonlinear lumped mechanical continuous-time systems. The model structure used in this iterative learning control procedure is new and combines a linear state space model and a nonlinear feature space transformation. An intuitive two-step iterative algorithm to identify the model parameters is presented. It alternates between the estimation of the linear and the nonlinear model part. It is assumed that besides the input and output signals also the full state vector of the system is available for identification. A measurement and signal processing procedure to estimate these signals for lumped mechanical systems is presented. The iterative learning control procedure relies on the calculation of the input that generates a given model output, so-called offline model inversion. A new offline nonlinear model inversion method for continuous-time, nonlinear time-invariant, state space models based on Newton's method is presented and applied to the new model structure. This model inversion method is not restricted to minimum phase models. It requires only calculation of the first order derivatives of the state space model and is applicable to multivariable models. For periodic reference signals the method yields a compact implementation in the frequency domain. Moreover it is shown that a bandwidth can be specified up to which learning is allowed when using this inversion method in the iterative learning control procedure. Experimental results for a nonlinear single-input-single-output system corresponding to a quarter car on a hydraulic test rig are presented. It is shown that the new nonlinear approach outperforms the linear iterative learning control approach which is currently used in the automotive industry on durability test rigs.

Keywords: Multivariable nonlinear systems; Nonlinear system identification; Tracking control; Nonlinear iterative learning control; Nonlinear system inversion; Lumped mechanical systems

1. Introduction

In many control applications [1] the system dynamics can be approximated by a linear model with, often additive or multiplicative, uncertainty [2]. If these linear model uncertainties are too large the performance

*Corresponding author. Tel.: +32 16 322 540; fax: +32 16 322 987.
E-mail address: jan.swevers@mech.kuleuven.be (J. Swevers).

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that can be obtained with linear control techniques [2] will be moderate or insufficient. If this is the case, one has to resort to nonlinear models [3–5], nonlinear system identification [6–8,5] and nonlinear control techniques [9–11]. Usually however these nonlinear system identification methods generate models that do not satisfy the conditions and structure requirements imposed by the nonlinear control design techniques. For example most of the nonlinear control design methods assume that a physical continuous-time state space representation of the system is available [9–11], while the existing nonlinear system identification procedures generate discrete-time, black-box, input–output models [8]. In addition, usually no direct link between these different system representations exists, as there is for linear systems. This is a consequence of the fact that the class of nonlinear systems and models is very broad, or as Stanislaw Ulam, godfather of what is now known as nonlinear science, famously remarked [12]: ''Using the term 'nonlinear science' is like calling the bulk of zoology the study of non-elephants''.

This paper presents a new nonlinear state space model structure for nonlinear time-invariant (NLTI) multiple-input-multiple-output (MIMO or multivariable) systems. It consists of a linear and a nonlinear part. The nonlinear part uses so-called features to capture the nonlinear system characteristics in a black-box setting. The features discussed in this paper correspond to sigmoidal neurons [13,14], which have been shown to be successful in approximating complex nonlinear functions [15]. This paper focusses on NLTI lumped mechanical systems. It is shown that these systems typically contain important, physically interpretable, linear dynamics besides the nonlinear characteristics. To capture these dynamics within the linear part of the model, an intuitive two-step iterative identification algorithm to estimate the model parameters is presented. It alternates the estimation of the parameters of the linear and the nonlinear part of the model structure at each iteration. A similar modeling concept and two-step identification procedure are presented in [16,17]. The modeling approach presented in this paper is, however, more general since the nonlinear part is based on sigmoidal neurons. The nonlinear part of the model structure presented in [16,17] are static nonlinearities and NARX models, respectively. The main drawback of the presented modeling approach is that the nonlinear part is nonlinear in the unknown parameters hence requiring nonlinear techniques to estimate them with no guarantee for global convergence.

For the identification it is assumed that, besides the input and the output, also the states and their time derivatives are available. This is an important restriction for the application of the presented modeling approach. However, it is illustrated in this paper that by proper instrumentation this restriction can be overcome for lumped mechanical systems. This paper also presents a measurement and signal processing procedure to obtain accurate estimates of the states and their time derivatives for lumped mechanical systems based on sensor fusion. The combination of the new model structure with the intuitive two-step iterative identification algorithm yields a gray-box NLTI modeling approach [6]. The main advantage of this modeling approach is that the structure of the physical model of the system can be copied into the proposed model, while well established black-box estimation techniques are used to identify the nonlinear characteristics. This helps to keep the number of unknown model parameters low and yields physical state variables.

Accurate tracking control can be obtained using the nonlinear internal model control (NIMC) scheme of Economou [18] and Henson [19]. The NIMC scheme assumes that a (perfect) nonlinear model of the system and an (exact) inverse of that model are available. Currently the only method to calculate the inverse model of a nonlinear state space model was derived by Hirschorn [20] but is restricted to minimum phase systems having a well defined relative degree [9]. Hirschorn's method uses feedback linearization and requires the calculation of the model's higher order Lie derivatives which assumes smooth nonlinear characteristics. Moreover the NIMC scheme assumes closed loop stability under the assumption of a perfect model. In practice a model is never perfect such that stability of the nonlinear closed loop NIMC scheme should be imposed during the design. It is well known that this is an extremely difficult task. To avoid closed loop stability problems, feedforward control can be used to obtain accurate tracking control. Iterative learning control (ILC) aims at designing a feedforward signal by repeating the same control task and updating the control signal iteratively based on the system response measured during the previous iteration. With iterative learning, accurate tracking can be obtained even if the system model is uncertain. ILC is only applicable to systems that perform the same action repeatedly over a finite time interval. The research on linear iterative learning control (LILC), that is, ILC for linear systems or based on a linear model of the system, was initiated