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Structured Set Membership identification of nonlinear systems with application to vehicles with controlled suspension ☆

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Abstract

This paper considers an iterative algorithm for the identification of structured nonlinear systems. The systems considered consist of the interconnection of a MIMO linear systems and a MIMO nonlinear system. The considered interconnection structure can represent as particular cases Hammerstein, Wiener or Lur'e systems. A key feature of the proposed method is that the nonlinear subsystem may be dynamic and is not assumed to have a given parametric form. In this way the complexity/accuracy problems posed by the proper choice of the suitable parametrization of the nonlinear subsystem are circumvented. Moreover, the simulation error of the overall model is shown to be a nonincreasing function of the number of algorithm iteration. The effectiveness of the algorithm is tested on the problem of identifying a model for vertical dynamics of vehicles with controlled suspensions from both simulated and experimental data.

Keywords: Structured identification; Nonlinear systems; Controlled suspension vehicles

1. Introduction

In the paper, the problem of using data and physical information in the identification of complex nonlinear systems is investigated. Consider a discrete time MIMO system represented by a regression function $f_o = [f_o^1, \ldots, f_o^q]$ describing the time evolution of system output as

$$\begin{aligned} y_{t+1}^i &= f_o^i(w_t^i), \quad i = 1, \ldots, q, \\ w_t^i &= [y_t^i, \ldots, y_{t-n_y}^i, \\ &\quad u_t^1 \ldots u_{t-n_1}^1, \ldots, u_t^m, \ldots, u_{t-n_m}^m] \in \Re^{n_i}. \end{aligned} \tag{1}$$

Identification aim is to find estimates $\hat{f}$ of f_o from a set of noise corrupted measurements $\tilde{y}_t^i$ and $\tilde{w}_t^i$, $i = 1, \ldots, q, t = 1, 2, \ldots, T$ of outputs y_t^i and of regressors w_t^i, possibly minimizing some measure of the identification error $f_o - \hat{f}$. Because of finiteness of data, no finite bound or confidence interval can be derived for the identification error if no further information is available on $f_o(w)$. This information is typically given by assuming that it belongs to some parametric family $f(w, \theta)$ of functions. When possible, first principle laws are used to derive equations describing the evolution of the variable of interest, where the functional forms of involved nonlinear functions are known, depending on some unknown parameters θ. In other situations, due to the fact that the laws are too complex or not sufficiently known, this is not possible or not convenient and a black-box approach is taken, considering that f_o belongs to a suitably chosen parametrized set of functions $f(w, \theta) = \sum_{i=1}^r \alpha_i \sigma_i(w, \beta_i)$, $\beta_i \in \Re^q$, where $\theta = [\alpha, \beta]$ and the σ_i's are given functions, e.g. piece-wise linear, polynomial, sigmoidal, wavelet, etc. (Haber & Unbehauen, 1990; Isermann, Ernst, & Nelles, 1997; Narendra & Mukhopadhyay, 1997; Sjöberg et al., 1995). In both cases, physical or black-box modeling, the problem is reduced to estimating the parameters θ from data. This task may be performed by minimizing some suitable functional, as done e.g. in

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prediction error methods, which exhibit important statistical properties (Bauer & Ninness, 2002; Ljung & Caines, 1979). However, several problems may arise. The functional to be minimized may result in most cases not convex and trapping in local minima may occur, causing serious accuracy problems even in case of exact modeling, i.e. that $f_o(w) = f(w, \theta^o)$ for some "true" θ^o. Indeed, in general both first principle laws or black-box model selection procedures can give only approximate modeling of the involved phenomena, i.e. not completely correct information is provided to the identification procedure, since $f_o(w) \neq f(w, \theta)$, $\forall\theta$. The incorrect part of the assumed information may counteract the positive effects induced on identification accuracy by the correct part. Evaluating the overall balance of these two effects on the identification error, though actively investigated in the last decade for the case of linear systems (Chen & Gu, 2000; Milanese, Norton, Piet Lahanier, & Walter, 1996; Partington, 1991), is a largely open problem for nonlinear systems.

These considerations suggest the interest in identification methods able to account for different kinds of knowledge about the system, able to provide information which may be to a large extent considered correct. In many applications, this can be provided by information on the physical interconnection structure of the system to be identified, allowing its decomposition in subsystems, connected through unmeasured signals. Typical cases considered in the literature are Hammerstein, Wiener and Lur'e systems, consisting of two subsystems, a linear dynamic one and a nonlinear static one, connected in cascade or feedback form (Bai, 2002, 2003; Billings & Tsang, 1990; Crama & Shoukens, 2001; Lang, 1997). Among the many approaches proposed in the literature for the identification of such classes of systems, iterative algorithms have been proposed (see e.g. Narendra & Gallman, 1966; Rangan, Wolodkin, & Poolla, 1995; Stoica, 1981; Vörös, 1999) based on the fact that if the interconnecting signals are known, the identification problem reduces to the identification of each subsystems from their input–output data. The guesses on the interconnecting signal are then iteratively adapted on the base of the identified submodel at each iteration. Though their convergence properties are not completely understood (Crama & Shoukens, 2001; Narendra & Gallman, 1966; Rangan et al., 1995; Stoica, 1981; Vörös, 1999) these algorithms proved to give satisfactory results in many simulated and real problems.

In this paper we propose an iterative algorithm, based on the same principle, able to deal with more complex interconnection structures which may arise in practical applications, where the nonlinear subsystems may be dynamic.

A key feature of the method is that the nonlinear dynamic subsystems are not supposed to have a given parametric model. In this way the above discussed problems posed by the proper choice of a suitable parametrization and the drawbacks related to the effects of approximate modeling are circumvented. Moreover, the simulation error of the overall model is shown to be a nonincreasing function of iterations. Indeed, the algorithm may converge in few iterations to very satisfactory estimates even for quite rough initializations, as shown in the presented example, related to the identification of the vertical dynamics of vehicles with controlled suspensions. Two sets of data are used. The first set is composed of simulated data, thus allowing direct comparisons of identified subsystems and connecting signal with the "true" ones generating the data. The second set consists of experimental data acquired on a real car, thus showing that the proposed structured identification algorithm may prove to give quite good results in nontrivial real applications.

2. Structured experimental modeling

In the paper it is considered that the system to be identified, using information on its physical interconnection, can be represented by the decomposition structure of Fig. 1.

All the signals u, y, v may be multivariable. Submodels M_1 and M_2 are dynamic MIMO discrete time systems, one linear and the other nonlinear. The problem is to identify M_1 and M_2, supposing that noise corrupted measurements $\tilde{u} = [\tilde{u}_1, \ldots, \tilde{u}_T]$ and $\tilde{y} = [\tilde{y}_1, \ldots, \tilde{y}_T]$ of input and output sequences are available, but the interconnecting sequence $v = [v_1, v_2, \ldots]$ is unknown.

Note that this structure allows to represent widely studied classes of models such as: Hammerstein models, where M_1 is a static nonlinearity $v(t) = f(u(t))$ not depending on y and M_2 is linear dynamic; Wiener models, where M_2 is a static nonlinearity $y(t) = f(v(t))$ and M_1 is linear dynamic with transfer function from y to v equal to zero; Lur'e models, where M_1 is a static nonlinearity $v(t) = f(u(t) - v(t))$ and M_2 is linear dynamic. Indeed, more complex structures can be represented as well, e.g. the one of Fig. 6, arising in modeling vehicles vertical dynamics.

Assuming parametric forms $M_1(\theta_1)$ and $M_2(\theta_2)$ for the two subsystems, estimates of θ_1, θ_2 can be obtained e.g. by prediction error methods. Even if linear parametrizations are adopted for M_1 and M_2, the overall optimization problem is not convex, possibly leading to poor identification results because of trapping in local minima. Alternative iterative procedures have been proposed for the identification of Hammerstein or Wiener models, based on the fact that if interconnecting signal v is known, the problem reduces to estimation of $M_1(\theta_1)$ and $M_2(\theta_2)$ from

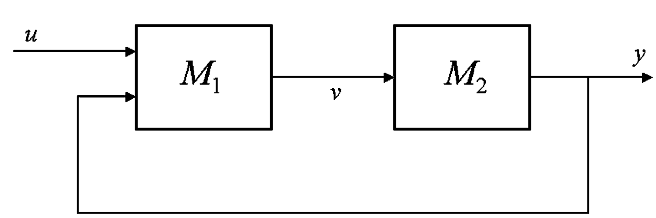

Fig. 1. Structure decomposition.