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Identification of a Benchmark Wiener–Hammerstein: A bilinear and Hammerstein–Bilinear model approach

P. Lopes dos Santos [a,*], José A. Ramos [b], J.L. Martins de Carvalho [c]

[a] Faculdade de Engenharia da Universidade do Porto, Rua Dr Roberto Frias s/n, 4200-465 Porto, Portugal
[b] Farquhar College of Arts and Sciences, Division of Mathematics, Science, and Technology, Nova Southeastern University, 3301 College Avenue, Fort Lauderdale, FL 33314, United States
[c] Faculdade de Engenharia da Universidade do Porto, Rua Dr Roberto Frias s/n, 4200-465 Porto, Portugal

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ABSTRACT

In this paper the Wiener–Hammerstein Benchmark is identified as a bilinear discrete system. The bilinear approximation relies on both facts that the Wiener–Hammerstein system can be described by a Volterra series which can be approximated by bilinear systems. The identification is performed with an iterative bilinear subspace identification algorithm previously proposed by the authors. In order to increase accuracy, polynomial static nonlinearities were added to the bilinear model input. These Hammerstein type bilinear models are then identified using the same iterative subspace identification algorithm.

1. Introduction

Nonlinear systems are often represented as the interconnection of Linear Time Invariant (LTI) Systems and static (memoryless) nonlinearities. These model structures, known as block oriented models, have the ability capture the dynamics of a large class of nonlinear systems. As a result, in the last decades a significant amount of research has been carried out on the identification of these class of models. The most simple and common structures are the Hammerstein and the Wiener models. The first one, was introduced in 1930 by Hammerstein (1930) and consists in a nonlinear static block in series with an LTI system. In the second one, proposed in 1958 by Wiener (1958), the nonlinear block follows the linear one. Despite their simplicity, these structures accurately describe a wide variety of nonlinear systems such as distillation columns and heat exchangers (Eskinat, Johnson, & Luyben, 1991), electrical drives (Balestrino, Landi, Ould-Zmirli, & Sani, 2001), solid oxide fuel cells (Jurado, 2006), magneto-rheological dampers for vibration suppression (Wang, Sano, Chen, & Huang, 2009), biomedical systems such stretch reflex electromyogram (EMG) data recorded from spinal cord injured patients (Dempsey & Westwick, 2004), biological systems (Hunter & Korenberg, 1986), etc. Consequently, they have attracted much interest in the control and identification area. There are several approaches to Hammerstein systems identification such as correlation (Billings & Fakhouri, 1979; Hunter & Korenberg, 1986), relay–feedback (Balestrino et al., 2001) optimization (Dempsey & Westwick, 2004; Ding & Chen, 2005; Eskinat et al., 1991; Jurado, 2006) and subspace (Verhaegen & Westwick, 1996) methods. Both the relay and feedback methods require special input signals (Gaussian for the former and binary and multistep for the latter) somehow restricting their application range. Optimization methods differ in the way they model the nonlinearity, the LTI model and the optimization algorithm. Good results are achieved with the nonlinearity modeled as a linear combination of basis functions (Dempsey & Westwick, 2004; Ding & Chen, 2005; Jurado, 2006), ARMAX (Ding & Chen, 2005; Eskinat et al., 1991; Schoukens, Widanage, Godfrey, & Pintelon, 2007), Box Jenkins (Schoukens, Widanage et al. 2007),orthonormal transfer functions basis (Jurado, 2006) and state-space (Verhaegen & Westwick, 1996) LTI models. The optimization of ARMAX and Box Jewnkins LTI models is performed by iterative (Eskinat et al., 1991) or recursive (Ding & Chen, 2005) algorithms that require good initial models (see Schoukens, Widanage et al., 2007 for a good initialization method for Hammerstein system identification methods). Hammerstein with the nonlinearity represented by a linear combination of nonlinear basis functions and the LTI described with an orthonormal transfer functions basis model may be efficiently identified by a non-iterative least square estimator (Jurado, 2006). Subspace methods are also non-iterative methods that usually lead to accurate models (Verhaegen & Westwick, 1996).

* Corresponding author. Tel.: +351 22 5081789.
E-mail addresses: pjsantos@fe.up.pt (P. Lopes dos Santos), jr1284@nova.edu (J. A. Ramos), jmartins@fe.up.pt (J.L. Martins de Carvalho).

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Boyd and Chua (1985) have shown that Wiener models are capable of representing with arbitrary accuracy any time invariant system with a fading memory. On the other hand, they also can faithfully depict several physical realities. Consequently, a wide range of nonlinear systems may be described by these models and they have been successfully used in many engineering and science fields such as electronics and wireless communications (Clark, Chrisikos, Muha, Moulthrop, & Silva, 1998), chemical industry (Bruls, Chou, Haverkamp, & Verhaegen, 1999; Kalafatis, Wang, & Cluett, 1997), semiconductor manufacturing (Tian & Fujii, 2005), biology (Hunter & Korenberg, 1986), biomedical engineering (Celka & Colditz, 2002), etc. It is well known that if the input is Gaussian noise, then the LTI subsystem identification can be separated from the nonlinear block. Based on this result, several LTI identification methods were adapted to Wiener systems (Billings & Fakhouri, 1982; Bruls et al., 1999; Greblicki, 1994; Hu & Chen, 2005; Westwick & Verhaegen, 1996). However, the Gaussian assumption for the input signal is too restrictive in practical applications and therefore other approaches were proposed. Some are based on the invertibility of the nonlinearity (Bruls et al., 1999; Hunter & Korenberg, 1986; Kalafatis et al., 1997; Zhang et al., 2006) which is also a quite restrictive assumption because many output nonlinearities in real world problems are non-invertible. These restrictions do not exist in the algorithms proposed by Bai and Reyland (2008), Wigren (1993), Tian and Fujii (2005), Cerone and Regruto (2005), and Hagenblad, Ljung, and Wills (2008). Still, the method proposed in Bai and Reyland (2008) requires a white noise input signal while the others only need that an input signal with adequate excitation. Wigren (1993) approximated the nonlinearity by a piecewise linear function and the LTI system was modeled by a transfer function. Only white measurement noise was considered and the parameters where estimated through the minimization a quadratic criterion of the output error by a recursive algorithm. Tian and Fujii (2005) also used a recursive algorithm but they described the LTI subsystem by a state-space model. The system was assumed to be disturbed by process and measurement white noises and a prediction error quadratic loss function was minimized by the Extended Kalman Filter algorithm (Ljung, 1997). The nonlinearity was approximated by a linear combination of Tchebychev polynomials. In Cerone and Regruto (2005) a Wiener system with an LTI input/output model and a polynomial nonlinearity disturbed by output bounded noise was considered. In Hagenblad et al. (2008) it has been shown that if only output noise is assumed, biased estimates may be obtained in common real life situations where disturbances are also present before the nonlinearity. The Likelihood function for the problem was formulated and an algorithm was proposed for its maximization. The consistency of this Maximum Likelihood estimator has been proved but the algorithm initialization was left as an open problem.

Model structures with a static nonlinearity sandwiched between two LTI systems are known as Wiener–Hammerstein models. Nonlinear system identification of this model structure has been studied for many years. Existing approaches can be roughly divided in the following classes: (i) nonparametric time domain methods (Billings & Fakhouri, 1978, 1980, 1982; De Brabanter, 2009; Fakhouri, 1980a,b; Falck, Pelckmans, Suykens, & De Moor, 2009; Korenberg & Hunter, 1986; Marconato & Schoukens, 2009; Pillonetto & Chiuso, 2009), (ii) parametric time-domain input/output methods (Bershad, Bouchired, & Castanie, 2000, 2001; Boutayeb & Darouach, 1995; Chen & Fassois, 1997; Emara-Shabaik, Ahmed, & Al-Ajmi, 2002; Moustafa & Emara-Shabaik, 2000; Piroddi, Farina, & Lovera, 2009; Truong & Wang, 2009; Vörös, 2007; Wills & Ninness, 2009), (iii) parametric time domain state-space methods (Ase, Katayama, & Tanaka, 2009; Lopes dos Santos, Ramos, & Martins de Carvalho, 2009a; Paduart, Lauwers, & Pintelon, 2009; Van Mulders, 2009), (iv) frequency domain methods (Brillinger, 1977; Crama & Schoukens, 2005; Goodman, Herman, Bond, & Miller, 2009; Lauwers, Pintelon, & Schoukens, 2009; Schoukens, Pintelon, & Enqvist, 2007; Tan & Godfrey, 2002). These approaches make use of techniques such us correlation (Billings & Fakhouri, 1978, 1980, 1978; Fakhouri, 1980a,b) and/or Fourier analysis (Billings & Fakhouri, 1978; Crama & Schoukens, 2005; Goodman et al., 2009; Schoukens, Pintelon et al. 2007; Tan & Godfrey, 2002), optimization and/or subspace based (Ase et al., 2009; Bershad et al., 2000; Lopes dos Santos et al., 2009a; Paduart et al., 2009; Van Mulders, 2009; Wills & Ninness, 2009),machine learning (De Brabanter, 2009; Falck et al., 2009; Marconato & Schoukens, 2009), etc. In 2009, an invited session on a Wiener–Hammerstein Benchmark for nonlinear identification was organized for the SYSID 2009. The objective of this benchmark is "to compare different black-box identification methods to model nonlinear systems" in order "to get a better understanding about the capabilities of different modeling and identification methods" (Schoukens, Suykens, & Ljung, 2008). Twelve papers were presented with methods ranging from the traditional frequency response analysis to recent learning theory algorithms (Ase et al., 2009; De Brabanter, 2009; Falck et al., 2009; Lauwers et al., 2009; Lopes dos Santos, Ramos, & Martins de Carvalho, 2009b; Marconato & Schoukens, 2009; Paduart et al., 2009; Pillonetto & Chiuso, 2009; Piroddi et al., 2009; Truong & Wang, 2009; Van Mulders, 2009; Wills & Ninness, 2009).

It is well known that a bilinear system can approximate lower order kernels of nonlinear systems Volterra series expansion (Bruni, DiPillo, & Koch, 1974; Desai, 1986; Favoreel, 1999; Hsu, Desai, & Crawley, 1985; Isidori, 1973). However, when the high order Volterra kernels are significant bilinear systems may have poor fit. Thus, these models can only describe a limited class of nonlinear systems. Despite this limitation, they still provide a higher degree of approximation to nonlinear models than traditional linear models. On the other hand, the type of nonlinearity that these systems exhibit makes their structure one of the simplest and, in some sense, the closest to linear systems. This allows the application of several techniques and procedures already developed for linear systems (Bruni et al., 1974). Moreover, since a bilinear system can be seen as a Linear Parameter Varying (LPV) System with the input signal as the scheduling parameter, they also benefit from the recent development of LPV techniques. See Tóth (2010) for an excellent survey on LPV system modeling, identification and control methods.

In this work we show that it is possible to model the Wiener–Hammerstein Benchmark system with a Hammerstein–Bilinear model. This is done by comparing the Volterra series of both the Wiener–Hamerstein and the bilinear system. From this comparison it is concluded that the introduction of *fictional* inputs $u(k)^2, u(k)^3, \ldots$, leads to a more accurate approximation. This result may be extended for any Wiener–Hammerstein system provided that the nonlinearity can be expanded in a MacLaurin series.

The Wiener–Hammerstein system benchmark is then identified with discrete Hammerstein–Bilinear models with several degrees in the input polynomial. We then verified that the mean square errors of the identified models decrease with the degree of the polynomial.

The Hammerstein–Bilinear models were estimated by an iterative subspace algorithm previously proposed by the authors in Lopes dos Santos, Ramos, and Martins de Carvalho (2005) and Lopes dos Santos et al. (2009b). This paper is a more complete version of Lopes dos Santos et al. (2009a) presented in the SYSID 2009 Benchmark session.

The paper is organized as follows. In Section 2 the benchmark problem is described. The bilinear and the Hammerstein type