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Survey paper

Identification of block-oriented nonlinear systems starting from linear approximations: A survey☆

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ABSTRACT

Block-oriented nonlinear models are popular in nonlinear system identification because of their advantages of being simple to understand and easy to use. Many different identification approaches were developed over the years to estimate the parameters of a wide range of block-oriented nonlinear models. One class of these approaches uses linear approximations to initialize the identification algorithm. The best linear approximation framework and the ϵ-approximation framework, or equivalent frameworks, allow the user to extract important information about the system, guide the user in selecting good candidate model structures and orders, and prove to be a good starting point for nonlinear system identification algorithms. This paper gives an overview of the different block-oriented nonlinear models that can be identified using linear approximations, and of the identification algorithms that have been developed in the past. A non-exhaustive overview of the most important other block-oriented nonlinear system identification approaches is also provided throughout this paper.

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1. Introduction

Nonlinear models are often used to obtain a better insight into the behavior of the system under test, to compensate for a potential nonlinear behavior using predistortion techniques, or to improve plant control performance. Popular nonlinear model structures are, amongst others, nonlinear state space models (Paduart, 2008; Schön, Wills, & Ninness, 2011; Suykens, De Moor, & Vandewalle, 1995), NARX and NARMAX models (Billings, 2013; Leontaritis & Billings, 1985), and block-oriented nonlinear models (Giri & Bai, 2010). Due to the separation of the nonlinear dynamic behavior into linear time invariant (LTI) dynamics and the static nonlinearities (SNL), block-oriented nonlinear models are quite simple to understand and easy to use.

This paper provides a survey of the identification of block-oriented nonlinear models using input–output data only. The identification algorithms that are discussed in this paper are all initialized using linear approximation frameworks for nonlinear systems: the Best Linear Approximation (BLA) (Enqvist, 2005; Enqvist & Ljung, 2005; Pintelon & Schoukens, 2012) and the ϵ-approximation (Schoukens, Pintelon, Rolain, Schoukens, Tiels, Vanbeylen, Van Mulders, & Vandersteen, 2015a) framework. An overview on the practical use of the BLA is provided in Schoukens, Vaes, and Pintelon (2016a), however, that paper does not address the use of the BLA for block-oriented nonlinear modeling purposes. Many other block-oriented identification approaches, different from the linear approximation approaches, are described in the literature (e.g. overparametrization, iterative, or kernel-based methods). A non-exhaustive overview of the most important approaches for each model structure is given at the beginning of each section discussing that particular model structure. The presented identification approaches and the considered block-oriented structures go beyond the methods and structures that previous surveys, such as Billings (1980) Giri and Bai (2010) Hasiewicz, Mzyk, Śliwiński and Wachel (2012), present.

Block-oriented identification approaches starting from linear approximations have the advantage of addressing part of the model selection problem in an LTI-framework, which is better understood by many practitioners. These approaches obtain good

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results in various benchmark problems (such as the Wiener–Hammerstein (Schoukens, Suykens, & Ljung, 2009b) and Silverbox benchmarks (Wigren & Schoukens, 2013)), as illustrated in Section 12 of this paper. Linear models of nonlinear systems can also be used to detect the underlying block-oriented structure of the system under test. Haber and Unbehauen (1990), Lauwers, Schoukens, Pintelon, and Enqvist (2008) and Schoukens et al. (2015a) discuss this structure detection problem using linear approximations, however, they do not present identification approaches there.

The different block-oriented structures that are studied throughout this paper are introduced in Section 2. Bussgang's theorem is very useful for determining the BLA of many block-oriented structures. This theorem is discussed in Section 3. The considered linear approximation frameworks are discussed next in Section 4. Section 5 introduces the cost function that is considered throughout this paper. The identification algorithms for the single branch models (Hammerstein, Wiener, Hammerstein–Wiener and Wiener–Hammerstein) are studied in Section 7. The parallel block-oriented nonlinear modeling approaches are discussed in Section 8. Section 9 considers the identification of different nonlinear feedback models. Section 10 provides an overview of the pros and the cons of the model structures and their identification based on the BLA. Some guidelines for the user are presented in Section 11. The good performance of the identification methods discussed in this paper is illustrated by some benchmark results in Section 12. Finally, some open research problems are highlighted in Section 13.

2. Block-oriented nonlinear models: Structures, representation and noise framework

Model structures

Block-oriented nonlinear models are constructed starting from two basic building blocks: a linear time-invariant (LTI) block and a static nonlinear block. They can be combined in many different ways. Series, parallel and feedback connections are considered in this paper, resulting in a wide variety of block-oriented structures as is depicted in Fig. 1. These block-oriented nonlinear models are only a selection of the many different possibilities that one could think of. For instance, this paper does not consider the generalized Hammerstein–Wiener structure that Wills and Ninness (2012) discuss, nor the Hammerstein/nonlinear feedback model structure that Van Pelt and Bernstein (2001) discuss. A comparison of the model complexity and the identification procedures of the considered model structures is made in Section 10.

Model representation

The LTI blocks and the static nonlinear blocks can be represented in many different ways. The LTI block could for instance be modeled as a nonparametric frequency response function (Giri, Rochdi, Radouane, Brouri, & Chaoui, 2013) or an impulse response (Lacy & Bernstein, 2003), or they can be parametrized using a state space (Verhaegen & Westwick, 1996), rational transfer function (Narendra & Gallman, 1966), or basis function expansion (Tiels & Schoukens, 2014). The static nonlinear block can again be represented in a nonparametric way using, for instance, kernel-based methods (Mzyk, 2014), or in a parametric way using, for instance, a linear in the parameters basis function expansion (polynomial, piecewise linear, radial basis function network, ...) (Schoukens, Pintelon, & Rolain, 2014a), neural networks (Schoukens, Marconato, Pintelon, Vandersteen, & Rolain, 2015b), or other dedicated parametrizations for static nonlinear functions.

The methods that are presented in this paper will typically use, but are not limited to, a rational transfer function representation for the LTI blocks and a linear in the parameters basis function expansion for the static nonlinearity.

Another issue of block-oriented nonlinear models is the uniqueness of the model parametrization. Gain exchanges, delay exchanges and equivalence transformations are present in many block-oriented structures (Schoukens, 2015; Schoukens et al., 2015b). This results in many different models with the same input–output behavior, but with a different parametrization. The Jacobian of the cost function can be rank deficient due to these indistinguishability issues that are common for block-oriented identification problems. The related degenerations in the Jacobian need to be taken into account during the optimization.

The indistinguishability issues do not only impact on the parametrization of the chosen model structure, they also affect the model structures themselves. The simple feedback structure (see Fig. 1) can both be represented using an LTI block in the forward path and a static nonlinearity in the feedback path, or the other way around, a static nonlinearity in the forward path and an LTI block in the feedback path as is depicted in Fig. 2. Both model structures lead to the same input–output representation, but are structurally different (Schoukens, Gommé, Van Moer, & Rolain, 2008). Indeed, we have that the outputs of the two possible simple feedback structures are given by:

$$\begin{cases} y(t) = G(q)\left[u(t) - g(y(t))\right], \\ \bar{y}(t) = \bar{g}\left(u(t) - \bar{G}(q)\bar{y}(t)\right). \end{cases} \tag{1}$$

Both representations should have the same input–output relationship, which results in the following equation:

$$G^{-1}(q)y(t) + g(y(t)) = \bar{g}^{-1}(y(t)) + \bar{G}(q)y(t). \tag{2}$$

It can be easily observed that this equation holds for $\bar{G}(q) = G^{-1}(q)$ and $\bar{g}(.) = g^{-1}(.)$. It is assumed here that both $G(q)$ and $g(y)$ are invertible. Note that the equivalence transformation can introduce an unstable (when $G(q)$ is not minimal-phase) and non-causal LTI block (when $G(q)$ contains a pure delay).

Noise framework

Assumption 1 (*Noise Framework*)**.** A Gaussian additive, colored zero-mean noise source $n_y(t)$ with a finite variance σ^2 is present at the output of the system only:

$$y(t) = y_0(t) + n_y(t). \tag{3}$$

This noise $n_y(t)$ is assumed to be independent of the known input $u(t)$. The signal $y(t)$ is the actual output signal and a subscript 0 denotes the exact (unknown) value.

The choice of the noise framework that is described in Assumption 1 is a simplified representation of reality. This simplification can lead to biased estimates when there are other noise sources present, located at other positions inside the system, e.g. process noise passing through a nonlinear subsystem (Hagenblad, Ljung, & Wills, 2008). A more realistic noise framework can be obtained by introducing multiple noise sources, or by placing the noise source at a different location in the considered system structure. For instance, Hagenblad et al. (2008), Lindsten, Schön, and Jordan (2013), Wahlberg, Welsh, and Ljung (2014) and Wills, Schön, Ljung, and Ninness (2013) consider multiple noise sources. This more realistic noise framework comes often at the cost of a more complex identification algorithm.

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