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Identification of Hammerstein model using functional link artificial neural network

Mingyong Cui [a], Haifang Liu [a], Zhonghui Li [a], Yinggan Tang [a,b,*], Xinping Guan [c]

[a] Institute of Electrical Engineering, Yanshan University, Qinhuangdao, Hebei 066004, China
[b] Key Laboratory of System Control and Information Processing, Ministry of Education, Shanghai 200240, China
[c] Institute of Electronic, Information, and Electrical Engineering, Shanghai Jiaotong University, Shanghai 200240, China

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ABSTRACT

In this paper, a novel algorithm is developed for identifying Hammerstein model. The static nonlinear function is characterized by function link artificial neural network (FLANN) and the linear dynamic subsystem by an ARMA model. The utilization of FLANN can not only result in a simple and effective representation of static nonlinearity but also simplify the learning algorithm. A two-step procedure is adopted to identify Hammerstein model by using a specially designed input signal, which separates the identification of linear part from that of nonlinear part. Levenberg–Marquart algorithm is used to learn the weights of FLANN. Simulation examples demonstrate the effectiveness of the proposed method.

1. Introduction

The dynamics of most practical systems are nonlinear in nature. It remains to be a challenging problem to accurately build models for such systems and processes. Block-oriented models, such as Hammerstein model, Wiener model and their combinations, had been adopted by many researchers to model practical systems due to their simple structure and effectual reflection of nonlinear dynamic systems. The Hammerstein model, which comprises a nonlinear static function followed by a linear dynamical subsystem (see in Fig. 1), has been successfully used to describe a large number of nonlinear systems like pH neutralization process [1], spark ignition engine torque [2], electrically stimulated muscle [3], continuous stirred tank rector [4], and fuel cell [5].

In the literature, many methods have been proposed to identify Hammerstein model. One difficulty associated with Hammerstein model identification is that the intermediate signal between the static nonlinearity and the linear subsystem is unavailable. To alleviate this difficulty, an iterative method was proposed by Narendra and Gallman in [6] for the identification of Hammerstein model with polynomial static nonlinearity. The iterative methods replace the intermediate signal with its estimation, i.e. the estimated output of linear dynamic subsystem. Then, the parameters of Hammerstein model are updated using the estimated intermediate signal. This method had been adopted by several authors to identify block-oriented nonlinear systems. For example, Vörös developed an iterative algorithm to identify Hammerstein model with two-segment polynomial nonlinearity in [7]. In [8], Ding et al. adopted the idea of iterative method to identify Hammerstein system, in which a Newton recursive and a Newton iterative identification algorithm are derived based on the gradient search algorithm. A gradient-based iterative algorithm for Hammerstein system identification was proposed in [9]. In [10], the identification of Hammerstein output error moving average (OEMA) system was considered. A data-filtering based recursive least square algorithm was proposed based on the idea of iterative method. In [11], Wang and Ding proposed a least square based and a gradient based iterative algorithm, respectively, for Wiener system identification. A similar idea was also adopted in [12–15]. Also, the iterative method was adopted in [16] to identify Hammerstein–Wiener system. In [17], Han and de Callafon presented an iterative instrumental variable method to identify a closed-loop Hammerstein model, in which the static nonlinearity is approximated by a piecewise triangle function. Chen et al. proposed an iterative method to identify continuous-time Hammerstein model [18]. Although it is simple and effective, the iterative identification algorithms suffer from the problem that the estimated parameters are not theoretically guaranteed to converge to their true values.

In [19], Chang and Luus proposed a non-iterative method to identify Hammerstein model with polynomial nonlinearity. The non-iterative methods can overcome the convergence difficulty of iterative methods [20]. However, the noniterative methods frequently lead to overparametrize the Hammerstein model. On the

* Corresponding author at: Institute of Electrical Engineering, Yanshan University, Qinhuangdao, Hebei 066004, China. Tel./fax: +86 335 8072979.
E-mail address: ygtang@ysu.edu.cn (Y. Tang).

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other hand, the identified parameters using noniterative algorithm are the product of the original system parameters, and a parameter separating technique such as singular value decomposition (SVD) [21,20] is needed to obtain the original parameters.

Another method for Hammerstein model identification is a two-step approach, which separates the identification of static nonlinearity from that of linear subsystem using a specially designed input signal. Sung suggested to use a pseudo-random binary sequence (PRBS) followed by a random multistep signal for continuous-time Hammerstein model identification [22]. This method was adopted by Bai [23,24] to identify discrete Hammerstein model. The advantage of this method is that it does not require any information about the non-measurable intermediate signal between the nonlinear and linear parts. Recently, heuristic search algorithms have also been adopted to identify Hammerstein model. In [25], the bacterial foraging optimization was used to identify Hammerstein model corrupted by color noise. In [26], two improved particle swarm optimization (PSO) algorithms were used to identify Hammerstein model, where the static nonlinear function is represented by FLANN. In [27], a non-uniform rational B-spline network (NURBSN) based method was proposed for Hammerstein model identification, where PSO was adopted to optimize the parameters of NURBSN.

In many methods mentioned above, some rigorous restrictions are imposed on the static nonlinear functions, for example, the form of nonlinearity is known [18,22] or the nonlinearity is invertible. In practice, the static nonlinearities are unknown. Furthermore, the nonlinearities are versatile and cannot be represented by a certain nonlinear function. Therefore, *a simple and effective* representation of static nonlinear nonlinearity is very important for the identification of Hammerstein model. In the literature, many tools are used to represent static nonlinear function. Least square support vector machines (LS-SVMs) [28,29], neuro-fuzzy model [30], non-uniform rational B-spline network (NURBSN) [27], Bezier curves and Bernstein polynomials [31] are few examples. However, there are some problems in the above representations. For LS-SVMs, all the training samples are used as support vectors, this will lead to a great deal of computations and the obtained model is not parsimonious. As for neuro-fuzzy model [30], NURBN [27], and Bezier curves [31] are concerned, many extra parameters are needed to characterize these model themselves. However, determining these extra parameters is not an easy work, making the identification process more complicated. In [30], the antecedent parameters of neuro-fuzzy model are determined using clustering algorithm. In [27], the parameters of NURBSN including the number of basis functions, the polynomial order and the knots of spline are determined according to prior knowledge, while the shaping parameters of spline are obtained through PSO.

Neural networks are powerful tool for modelling nonlinear systems due to their excellent approximation ability. Among various neural networks, function link artificial neural network (FLANN) is a single layer neural network with faster convergence rate and lesser computational load than a multi-layer perceptron (MLP) structure [32]. In FLANN, the hidden layer is removed, which leads to a simple structure making the learning algorithm relatively simple. FLANN expands the input vector into a higher dimensional space through a set of linearly independent functions. As a result, the hyper-planes generated by the FLANN will provide a good discrimination capability in input data space. Owing to these advantages, FLANN had been widely used in many engineering fields such as active noise control [33], system identification and control [34,35], prediction of stock market indices [36,37], equalization of communication channel [38], and data classification [39].

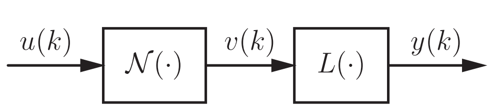

Fig. 1. The Hammerstein model.

To facilitate the identification of Hammerstein model, a new identification method is developed in this paper. In the proposed identification method, the static nonlinear part is represented by FLANN, which results in a simple representation of static nonlinearity without any extra parameters. Meanwhile, an effective and simple algorithm for FLANN learning can be conducted using this representation. The identification procedure consists of two stages. A specially designed signal is used as an input to separate the identification of linear part from that of nonlinear part. In the first stage, the parameters of linear dynamic subsystem are determined using the identification method of linear system. The static nonlinear part is identified in the second stage, where the weights of FLANN are learned through Levenberg–Marquart algorithm. The rest of this paper is organized as follows. In Section 2, FLANN based Hammerstein (FLANN-Hammerstein) model is introduced. The identification procedure of FLANN-Hammerstein model is described in detail in Section 3. Simulation examples are given in Section 4. Finally, conclusion remarks are given in Section 5.

2. FLANN based Hammerstein model

2.1. Hammerstein model

The Hammerstein model, as shown in Fig. 1, consists of a static nonlinear function followed by a linear dynamic subsystem. The model can be represented as

$$v(k) = \mathcal{N}(u(k)), \tag{1}$$

$$y(k) = \sum_{i=1}^{n_a} a_i y(k-i) + \sum_{j=1}^{n_b} b_j v(k-j), \tag{2}$$

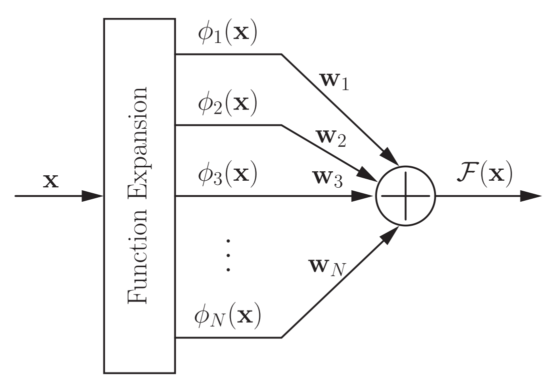

Fig. 2. The structure of FLANN.

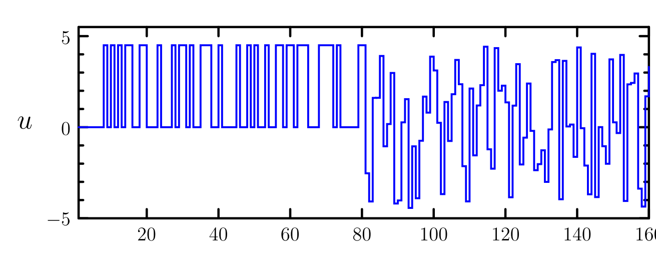

Fig. 3. Special input signal.