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Nonlinear system identification using a cuckoo search optimized adaptive Hammerstein model

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ABSTRACT

An attempt has been made in this paper to model a nonlinear system using a Hammerstein model. The Hammerstein model considered in this paper is a functional link artificial neural network (FLANN) in cascade with an adaptive infinite impulse response (IIR) filter. In order to avoid local optima issues caused by conventional gradient descent training strategies, the model has been trained using a cuckoo search algorithm (CSA), which is a recently proposed stochastic algorithm. Modeling accuracy of the proposed scheme has been compared with that obtained using other popular evolutionary computing algorithms for the Hammerstein model. Enhanced modeling capability of the CSA based scheme is evident from the simulation results.

1. Introduction

Modeling of nonlinear systems is of significant importance to the scientific community as most of the natural systems offer a nonlinear behavior. Hammerstein model, which is essentially a nonlinear adaptive network followed by a dynamic linear network, has been shown to effectively model nonlinear systems (Eskinat, Johnson, & Luyben, 1991; Narendra & Gallman, 1966). The nonlinear block of the Hammerstein model can be any nonlinear network such as multi layer perceptron (MLP) (Back & Tsoi, 1992), multilayer feedforward neural networks (MFNN) (Ll-Duwaish & Nazmul Karim, 1997) or radial basis function (RBF) networks (Hachino, Deguchi, & Takata, 2004) and the dynamic linear part can be represented by an adaptive infinite impulse response (IIR) filter. In a conventional nonlinear system identification strategy, the adaptive weights of the nonlinear as well the linear blocks are updated using a gradient descent algorithm like the ones based on the popular least mean square (LMS) algorithm (Widrow & Stearns, 1985).

In an endeavour to improve the modeling accuracy as well as to prevent the local optima problem caused by the traditional gradient descent approaches, efforts have been made to solve the modeling task as an evolutionary computing algorithm based optimization problem. A genetic algorithm (GA) has been applied for modeling of bilinear (Wang & Gu, 2007) and feedback systems (Chang, 2006) as well as in identifying Hammerstein models (Akramizadeh, Farjami, & Khaloozadeh, 2002; Li, 1999). An RBF trained using GA has been reported in Hachino et al. (2004) to identify the nonlinear block of a Hammerstein model. A particle swarm optimization (PSO) algorithm based parameter identification has been reported for several classes of linear and nonlinear systems (He, Wang, & Liu, 2007; Majhi & Panda, 2013; Modares, Alfi, & Naghibi Sistani, 2010).

Yang and Deb (2009) has recently reported a new meta-heuristic algorithm inspired by the interesting breeding pattern of cuckoos. Several studies have revealed improved convergence pattern of CSA over other prominent evolutionary optimization approaches including GA, PSO and artificial bee colony (ABC) optimization algorithm (Civicioglu & Besdok, 2013). The improved efficiency of CSA in finding global optima solution has resulted in widespread use of CSA in diverse fields of research (Yang & Deb, 2014). Patwardhan et al. has lately applied CSA in improving the identification accuracy of feedback systems (Patwardhan, Patidar, & George, 2014). A CSA based chaotic system identification has been presented in Xiang-Tao and Ming-Hao (2012).

Functional link artificial neural network (FLANN), which is single layer neural network, has gained significant attention among the research community owing to its simplicity and efficiency in modeling nonlinear systems. FLANN has found applications in various fields including acoustics (George & Gonzalez, 2014), communication systems (Patra, Meher, & Chakraborty, 2009), finance (Majhi, Panda, & Sahoo, 2009) and instrumentation (Patra, Meher, & Chakraborty, 2011). Patra et al. has reported the improved capability of FLANN over MLP in modeling nonlinear dynamic systems

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(Patra, Pal, Chatterji, & Panda, 1999). FLANN has been shown to provide enhanced convergence behavior over RBF networks in a nonlinear channel equalization problem in Patra, Chin, Meher, and Chakraborty (2008). A FLANN trained using an artificial immune system (AIS) has been presented in Nanda, Panda, and Majhi (2010) to model the static nonlinear part of a Hammerstein model.

With an objective to simultaneously utilize the superior nonlinear modeling capability of a FLANN and the improved efficacy of the CSA in training systems, this paper presents a nonlinear system identification scheme using a FLANN-IIR model trained using a CSA. The proposed scheme needs tuning of only a few algorithm parameters, which makes the implementation simpler. In addition, the new scheme is envisioned to offer improved convergence with a reduced computational time. The rest of the paper is organized as follows. A brief introduction to nonlinear systems and its identification is made in Section 2. FLANN, the non-linear component of the Hammerstein model used in this paper is also discussed in the section. It is followed by an introduction to CSA in Section 3. The task of nonlinear system identification using Hammerstein model is formulated as a CSA based optimization problem in Section 4. An exhaustive simulation study is also conducted in Section 4. The concluding remarks are drawn in Section 5.

2. Hammerstein model based nonlinear system identification

As shown in Fig. 1, the nonlinear plant which needs to identified essentially consists of a nonlinear static system followed by a linear system. The input and output of the linear section of the nonlinear plant considered in this paper are related as

$$y(n) = \frac{B(z)}{A(z)}x(n-1) + \frac{C(z)}{A(z)}\eta(n), \tag{1}$$

where

$$A(z) = 1 + a_1 z^{-1} + \cdots + a_N z^{-N}, \tag{2}$$

$$B(z) = b_0 + b_1 z^{-1} + \cdots + b_M z^{-M}, \tag{3}$$

$$C(z) = c_0 + c_1 z^{-1} + \cdots + c_K z^{-K} \tag{4}$$

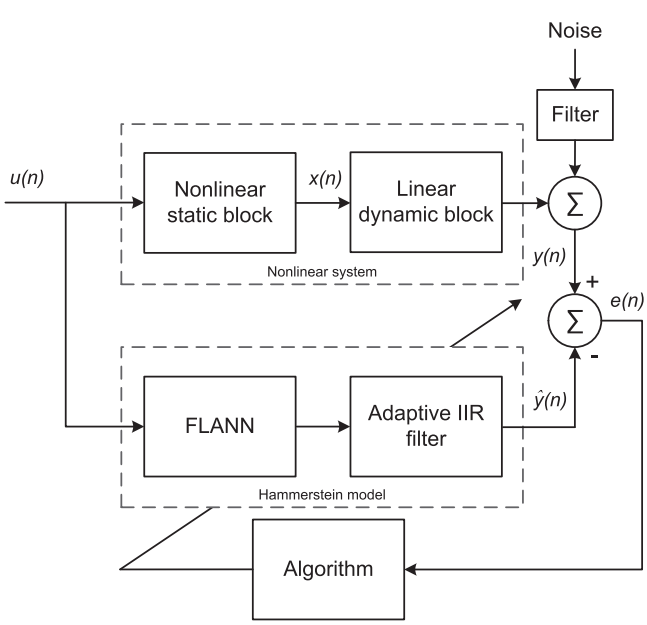

Fig. 1. Block diagram of nonlinear system identification using a Hammerstein model.

are transfer functions associated with the plant with orders N, M and K respectively. In (1), $y(n)$ is the output of the plant, $\eta(n)$ is the noise signal and $x(n)$ is the output of the static nonlinear block which is given by

$$x(n) = \rho[u(n)], \tag{5}$$

where $\rho(\cdot)$ represents the static nonlinearity and $u(n)$ is input to the nonlinear system. An attempt is made in this paper to identify the nonlinear plant using a Hammerstein model, which is a cascade of a FLANN and an adaptive IIR filter. The model considered is shown in Fig. 2. The system identification task primarily involves estimation of the nature and type of the static nonlinearity $\rho(n)$ as well as identifying the set of parameters $\boldsymbol{a}(n) = [a_1, a_2, \ldots, a_N]^{\mathrm{T}}$ and $\boldsymbol{b}(n) = [b_1, b_2, \ldots, b_M]^{\mathrm{T}}$ which constitute the dynamic linear section of the plant.

The static nonlinearity of the system is modeled using a FLANN, which is a single layer neural network. In a FLANN, the tap delayed input vector

$$\boldsymbol{d_u}(n) = [u(n), u(n-1), \ldots, u(n-Q+1)]^{\mathrm{T}} \tag{6}$$

is functionally expanded to a vector $\boldsymbol{u}(n)$ of length R. The functional expansion can be trigonometric (Patra et al., 1999), Chebyshev (Patra et al., 2002), Legendre (Patra et al., 2008) or power series. As can be observed from Fig. 2, the output of the FLANN is given by

$$\widehat{x}(n) = \boldsymbol{u}^{\mathrm{T}}(n)\boldsymbol{w}_1(n), \tag{7}$$

where $\boldsymbol{w}_1(n) = [\widehat{w}_1(n), \widehat{w}_2(n), \ldots, \widehat{w}_R(n)]^{\mathrm{T}}$ is the adaptive weight vector of the FLANN. The dynamic linearity of the system is modeled using an adaptive IIR filter. The input and output of linear dynamic model are related as

$$\widehat{y}(n) = \widehat{\boldsymbol{d}}_{\boldsymbol{x}}^{\mathrm{T}}(n)\widehat{\boldsymbol{b}}(n) + \widehat{\boldsymbol{d}}_{\boldsymbol{y}}^{\mathrm{T}}(n)\widehat{\boldsymbol{a}}(n), \tag{8}$$

where

$$\widehat{\boldsymbol{d}}_{\boldsymbol{x}}(n) = [\widehat{x}(n-1), \widehat{x}(n-2), \ldots, \widehat{x}(n-L)]^{\mathrm{T}} \tag{9}$$

is the tap delayed input vector of the IIR block, $\widehat{\boldsymbol{b}}(n) = \left[\widehat{b}_0(n), \widehat{b}_1(n), \ldots, \widehat{b}_{L-1}(n)\right]^{\mathrm{T}}$ is the adaptive weight vector of the feedforward section of the IIR filter, $\widehat{\boldsymbol{a}}(n) = \left[\widehat{a}_1(n), \widehat{a}_2(n), \ldots, \widehat{a}_P(n)\right]^{\mathrm{T}}$ is the weight vector of the feedback section and

$$\widehat{\boldsymbol{d}}_{\boldsymbol{y}}(n) = [\widehat{y}(n-1), \widehat{y}(n-2), \ldots, \widehat{y}(n-P)]^{\mathrm{T}} \tag{10}$$

is the tap delayed output signal vector. The complete adaptive weight vector of the linear block which needs to be updated is given by

$$\boldsymbol{w}_2(n) = \left[\widehat{\boldsymbol{b}}^{\mathrm{T}}(n), \widehat{\boldsymbol{a}}^{\mathrm{T}}(n)\right]^{\mathrm{T}}. \tag{11}$$

3. Cuckoo search algorithm

CSA, which is a recently reported evolutionary computing algorithm, is based on the breeding behavior of a special species of cuckoos (Yang & Deb, 2009). In addition to the breeding behavior, in a CSA, cuckoos have been assumed to follow a *Lévy* flight movement pattern. A *Lévy* flight is a movement along a straight line followed by sudden turns in random directions. These attributes of the CSA allows enhanced exploration of the search space in comparison with other evolutionary computing algorithms. CSA has been applied in diverse fields of engineering and technology including satellite image segmentation (Bhandari, Singh, Kumar, & Singh, 2014) and scheduling problems (Marichelvam, Prabaharan, & Yang, 2014). A particle filter trained using an improved CSA has been applied for target tracking in video signal processing (Walia & Kapoor, 2014). Vo et al. has applied CSA for