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Wavenet identification of dynamical systems by a modified PSO algorithm

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ABSTRACT

This paper presents a new method for the identification of nonlinear dynamical systems employing a wavelet neural network (wavenet) coupled to an infinite impulse response filter (WIIR). It is well known that a neural network trained by a gradient method is susceptible to fall in a minimum local. In order to solve this problem, we train the wavenet with a modified particle swarm optimization (mPSO) evolutionary algorithm, which integrates an elitist selection in order to conserve the best qualified particles. This approach is called mPSOWIIR algorithm. Basically, the idea is that the mPSO generates different sets of parameters that are evaluated in the dynamical system to be identified in order to obtain the fitness of every set. The best one and the best historical values of every set are taken into account to improve the set of parameters, keeping the diversity of new solutions and training the wavenet only with the first time steps of the dynamical system. This approach is able to reduce the number of possible solutions, avoid local minima and extend the search space of the wavenet; eluding the problem of finding good initial parameters by trial and error. One of the main features of the proposed method is that the number of parameters remains constant in all the training process. The mPSOWIIR algorithm is applied to identify nonlinear dynamical systems commonly used in specialized literature, obtaining satisfactory results.

1. Introduction

Math models of nonlinear dynamical systems can be obtained under ideal conditions. There are, however, unknown dynamics or external perturbations that cannot be modeled (Poznyak et al., 1999; Wang and Chen, 2006). These perturbations could be represented by some uncertain values. Many systems work in simulation, but in practice do not converge to obtain the same results. To solve this situation, many studies have used estimators, observers and adaptors to adjust their control laws to a number of dynamical systems (Poznyak et al., 1999; Wang and Chen, 2006; Lu, 2010; Ko, 2012a; Loussifi et al., 2016). The previous research demonstrates the relevance of dynamical system identification (Narendra and Parthasarathy, 1990; Poznyak et al., 1999; Ko, 2012b).

The combination of fuzzy logic, neural networks, wavelets theory and filter theory, have shown good results for the identification of dynamical systems (Lee and Teng, 2000; Abiyev and Kaynak, 2008; Zhao and Zhang, 2009a, b; Yilmaz and Oysal, 2010; Zhao et al., 2011; Mayorga et al., 2012; Ganjefar and Tofighi, 2015; Ramos et al., 2016). Nevertheless, trial-and-error tests are generally used to configure the proposed network and it only works for a reduced search space. At the same time, the training is mostly performed by a descendent gradient method, which is likely to fall in a minimum local (Ling et al., 2008a; Cheng and Bai, 2015; Lu et al., 2015).

In this line of investigation, some variants have been presented to obtain better identification results; some of them by implementing learning technics (Ko, 2013 adaptive, Ko, 2012a dynamical, Davanipoor et al., 2012 hybrids). These papers report improvements in decreasing the number of parameters in their fuzzy rules, or the numbers of epoch for the training stage.

Some research have incorporated optimization models using genetics algorithms (Reynolds, 1987; Juang, 2002). In particular, the application of the PSO evolutionary algorithm (Lin et al., 2008; Wei et al., 2010; Mandal et al., 2014; Vasundhara et al., 2014; Cheng and Bai, 2015) has reduced effectively the number of parameters and the computational cost. Nonetheless, in these previous works, there is no direct relationship between weighting matrices and nonlinear system characteristics, and selecting these matrices is done by trial and error based on designers experience (Amini et al., 2013); and the descendent gradient model is still used.

The main contribution of this manuscript is to propose a new structure of a WIIR that is able to adjust its dilatation, translation

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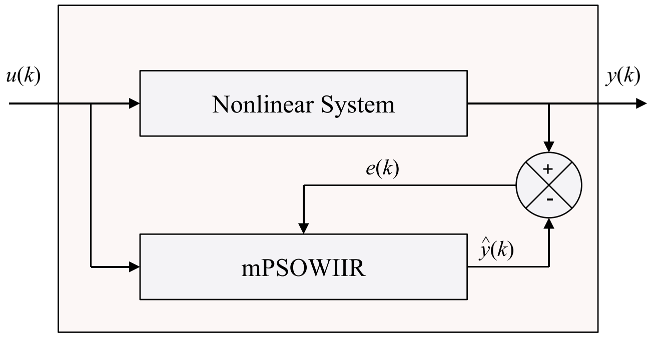

Fig. 1. Proposed scheme for identification of nonlinear systems using mPSOWIIR algorithm.

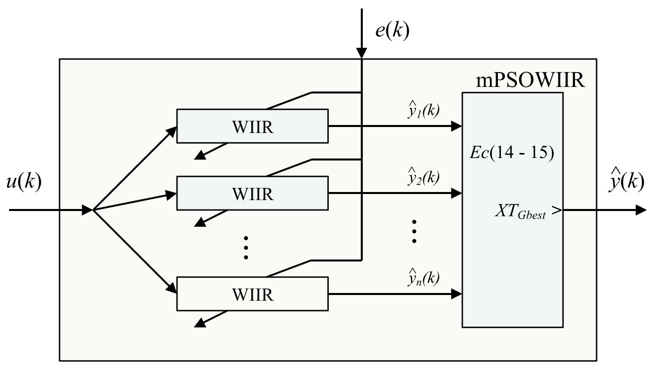

Fig. 2. Internal structure of the mPSOWIIR algorithm.

and weight parameters of the wavenet, without applying a gradient descendent method, where the coefficients of the filter are constants. This approach reduces the possibility of falling in local minima. The mPSO algorithm performs the training only during the first β samples of the plant, evaluating point by point the plant to identify the dynamical behavior. The best α-particles are kept in each step. We propose a population of individuals smaller than other works (Ko, 2012a; Ganjefar and Tofighi, 2015; Loussifi et al., 2016), reaching as well a fast and satisfactory convergence. Furthermore, the same structure of the WIIR is applied in all our computational experiments, and a large search space is defined in order to show that the wavenet is able to converge and reach a good dynamical identification, without need of finding good initial values by a trial-and-error procedure.

The conceptual application of the mPSO algorithm is simple. However, special attention must be taken in the numerical data management on coupling the mPSO algorithm with the wavenet neural network and the IIR filter, in order to conserve the data coherence in the identification process.

Plants commonly used in the literature for the identification and controls of dynamical systems (Narendra and Parthasarathy, 1991; Wang and Chen, 2006; Ebadat et al., 2011; Davanipoor et al., 2012; Ko, 2012b; Ganjefar and Tofighi, 2015) are employed to evaluate our proposal. This paper is organized as follow: Section 2 includes the basic concepts of wavenets for the identification of systems. Section 3 describes the PSO evolutionary algorithm. Section 4 presents the identification algorithm and Section 5 shows the computational results of the algorithm applied to plants commonly used in specialized literature. Finally, Section 6 gives some conclusions and perspectives of this work.

2. Identification of nonlinear systems using mPSOWIIR algorithm

The basic structure of the identification of single input-single output (SISO) nonlinear systems using mPSOWIIR algorithm is depicted in

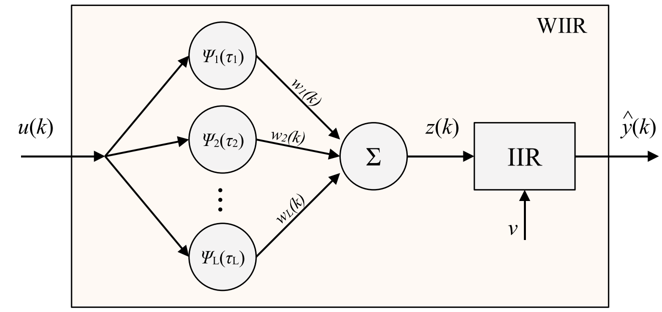

Fig. 3. Diagram of a WIIR, where $\psi_j(\tau_j) = \psi(\frac{k-b_j}{a_j})$, $1 \le j \le L$, is a daughter wavelet and v is a signal persistence.

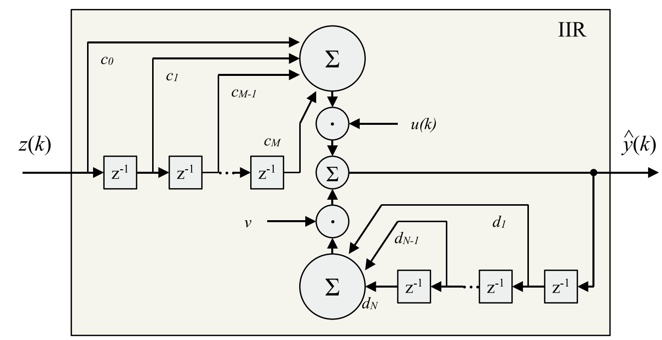

Fig. 4. IIR filter structure.

Fig. 1, where the inputs of mPSOWIIR block are the input of the nonlinear system $u(k)$ and the identification error $e(k)$, which is defined as the difference between output signal of the nonlinear system and the estimated output signal, i.e. $e(k) = y(k) - \hat{y}(k)$ and is used to train the WIIR. The internal structure of the mPSOWIIR algorithm is shown in Fig. 2.

The identification process is done by using a wavenet with an activation function $\psi(\tau)$ and their daughter wavelet functions $\psi_j(\tau)$. It is shown in Fig. 3. It also has one IIR filter in cascading structure, (see Fig. 4) that yields double improving speed of learning by pruning those nodes with insignificant relevant information from the cross contribution summation of daughters wavelets, located in the third layer; then with little or null contribution in the identification process, allowing a reduction in the number of iterations in the learning process (Panda et al., 2011; Mayorga et al., 2012; Upadhyaya et al., 2014).

The wavelet function $\psi(\tau)$ is called mother wavelet because different wavelets are generated from it by its expansion or contraction and translation, and the produced ones are called daughter wavelets $\psi_j(\tau_j)$, represented mathematically as:

$$\psi_j(\tau_j) = \frac{1}{\sqrt{a}}\,\psi(\tau_j) \tag{1}$$

where

$$\tau_j = \frac{k - b_j}{a_j} \tag{2}$$

where a is the scalar variable, which allows expansion and contraction, and b is the translation variable, which allows the displacement at instant k. Mayorga et al. (2012) have found that the best wavelet for approximation signal is the Morlet, which mathematical representation is (Daubechies, 1992):

$$\psi(\tau) = cos(\omega_0 \tau) e^{-0.5\ \tau^2}. \tag{3}$$