Expert Systems with Applications 37 (2010) 556–566

Contents lists available at ScienceDirect

Expert Systems with Applications

journal homepage: www.elsevier.com/locate/eswa

Development of efficient identification scheme for nonlinear dynamic systems using swarm intelligence techniques

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ARTICLE INFO

Keywords:
Swarm intelligence
Bio-inspired techniques
Identification of nonlinear and dynamic system and plants

ABSTRACT

This paper outlines the basic concept and principles of two simple and powerful swarm intelligence tools: the particle swarm optimization (PSO) and the Bacterial Foraging Optimization (BFO). The adaptive identification of an unknown plant has been formulated as an optimization problem and then solved using the PSO and BFO techniques. Using this new approach efficient identification of complex nonlinear dynamic plants have been carried out through simulation study.

1. Introduction

Nonlinear system identification of complex dynamic plants finds potential applications in many areas such as control, communication, power system and instrumentation. In recent years, modeling of real time processes has gained significant importance in these areas. Many interesting papers have been reported in the literature to identify both static and dynamic nonlinear systems. The Artificial Neural Network (ANN) has been applied for many identification and control tasks (Haykin, 1994; Parlos, Chong, & Atiya, 1994; Sastry, Santharam, & Unnikrishnan, 1994) but at the expense of large computational complexity. Narendra and Parthasarathy (1990) have employed the multiplayer perceptron (MLP) networks for effective identification and control of dynamic systems such as truck-backer-upper problem (Nguyen & Widrow, 1991) and robot arm control (Cembrano, Wells, Sarda, & Ruggeri, 1997). Subsequently the Radial Basis Function (RBF) network has been introduced (Poggio & Girosi, 1990) to develop system identification model of nonlinear dynamic systems (Chen, Billings, & Grant, 1992; Elanayar & Shin, 1994). One practical difficulty in this model is the selection of an appropriate set of RBF centres for effective learning. Further the wavelets in place of RBF has been suggested in neural network (Pati & Krishnaprasad, 1993; Zhang & Benveniste, 1992) to develop efficient identification models. The Functional Link Artificial Neural Network (FLANN), a computationally efficient single layer ANN, has been reported in the literature as an useful alterative to MLP for many applications. In the literature the trigonometric (Patra, Pal, Chatterji, & Panda, 1999) and Chebyshev (Patra & Kot, 2002; Purwar, Kar, & Jha, 2007) based FLANN architecture have been proposed for identification of nonlinear dynamic systems.

The swarm intelligence is the property of a system, whereby the collective behaviors of unsophisticated agents that are interacting locally with their environment create coherent global functional patterns. This type of intelligence is described by five principles such as proximity, quality, diverse response, stability and adaptability. Swarm intelligence provides a useful paradigm for complementing powerful adaptive systems. Both PSO and BFO algorithms belong to swarm intelligence and share few computational attributes. These are

(i) Individual elements are updated in parallel.
(ii) Each new value depends on its previous value as well as contribution from its neighbors.
(iii) All updates are performed according to the same rules.

In recent years evolutionary computational methods belonging to the swarm intelligence category have proven to be promising tools to solve many engineering and financial problems. These have been found to be powerful methods in domains where analytic solutions have not been proved to be effective. The Bacterial Foraging Optimization (BFO) (Passino, 2002) is one such evolutionary computing approach which is based on the foraging behaviour of *Escherichia coli* bacteria in our intestine. In this case foraging is considered as an optimization process in which the bacterium tries to maximize the collected energy per unit foraging time. The BFO has been successfully applied to many real world problems like harmonic estimation (Mishra, 2005), transmission loss reduction (Tripathy, Mishra, Lai, & Zhang, 2006), active power filter for load compensation (Mishra & Bhende, 2007), power network (Tripathy & Mishra, 2007), load forecasting (Ulagammai, Venkatesh, Kannan,

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doi:10.1016/j.eswa.2009.05.036

& Padhy, 2007), independent component analysis (Acharya, Panda, Mishra, & Lakhshmi, 2007), identification of nonlinear dynamic systems (Majhi & Panda, 2007a, 2007b; Panda, Majhi, & Mishra, 2006), stock market prediction (Majhi, Panda, Sahoo, & Das, 2007) and adaptive channel equalization (Majhi, Panda, & Choubey, 2006).

On the other hand the particle swarm optimization (PSO) is a population based, self adaptive search optimization technique first introduced by Kennedy and Eberhart in 1995. The development of this method is inspired by the social behavior of bird flocking and fish schooling. The PSO is a computational intelligence technique which is not much affected by the size or nonlinearity of the problem. Further, it can converge to optimal solution when any analytical methods fail to converge. The PSO is easier to implement as in this case few parameters need to be updated. It is also more efficient in maintaining diversity of the swarm. The PSO method is becoming very popular due to its simplicity of implementation and ability to quickly converge to a reasonably good solution. Various applications of the PSO algorithm are minimization of functions of many variables (Lu, Li, & Zhou, 2007), image segmentation (Borji, Hamidi, Moghadam, & Eftekhari, 2007; Liu, Sui, Zhang, Lu, & Liu, 2007), design of antennas (Baskar, Alphones, Suganthan, & Liang, 2005), nonlinear system identification (Panda, Mohanty, Majhi, & Sahoo, 2007), design of tree structures (Schutte & Groenwold, 2003), learning to play games (Messerschmidt & Engelbrecht, 2004) and multimodal biomedical image registration (Wachowiak, Smolikova, Zheng, Zurada, & Elmaghraby, 2004), design of adaptive IIR filters (Krusienski & Jenkins, 2004), identification of IIR systems (Majhi & Panda, 2009; Majhi, Panda, & Choubey, 2008), adaptive channel equalizer (Majhi & Panda, 2007a, 2007b) and stock market prediction (Majhi, Panda, Sahoo, & Panda, 2008).

The BFO and PSO are derivative free optimization tools in the sense that they do not need the computation of derivatives during training of the weights of the adaptive structure and therefore the solution is less likely to be trapped to local minima. On the other hand the least mean square (LMS) and the recursive least square (RLS) algorithms calculate the slope of the error surface at a current position in all directions, but moves in the direction of the most negative slope. Such optimization methods work satisfactorily when the error surface contains no local minima. But most of the real life problems are multimodal and also are distorted due to additive noise. In case of BFO there are number of parameters which are combinedly used for searching the total solution space. As a result the possibility of avoiding the local minima is higher. The distinct advantages of the BFO and PSO have motivated many researchers to use these tools for identification of complex nonlinear and dynamic systems. The connecting weights of the FLANN model are updated using BFO and PSO techniques instead of using derivative based algorithm. To facilitate the development of the new models efficient BFO and PSO based identification algorithms are proposed in this paper.

The paper is organized in seven sections. Section 2 introduces the adaptive identification problem. A generalized FLANN structure based identification model is given in Section 3. The trigonometric FLANN structure used in the identification model is shown in Fig. 2. The basic principle of BFO and PSO are dealt in Section 4. The algorithm required for identification of dynamic nonlinear system is developed and presented in Section 5. To validate the performance of the proposed model the identification of standard nonlinear dynamic systems is carried out through simulation and are presented in Section 6. In this section the results obtained from this study are also compared with those obtained by FLANN-BP based approach (Patra et al., 1999). Finally the conclusion of the proposed paper is outlined in Section 7.

2. Dynamic system identification of nonlinear systems

System identification is a fundamental problem in system theory. The problem of identification is related to the mathematical representation of a system. A model of a system is represented by an operator $\mathbf{P}$ from an input space $\mathbf{X}$ into an output space $\mathbf{Y}$ and the objective is to characterize the class P to which P belongs. The problem of identification is to obtain a class $\widehat{P} \subset P$ and an element $\widehat{\mathbf{P}} \in \widehat{P}$ so that $\widehat{P}$ approximates P in some predefined way. In static systems $\mathbf{X}$ and $\mathbf{Y}$ are subsets of R^n and R^m respectively. But in dynamical systems these are assumed to be bounded Lebesgue integrable function on the interval $[0, T]$ or $[0, \infty]$ (Narendra & Parthasarathy, 1990). The choice of the class of identification models and the specific methods used to determine $\widehat{P}$ is related to the desired accuracy and the analytical tractability. In many practical situations these decisions depend upon prior information concerning the plant to be identified.

The identification scheme of a dynamic nonlinear system is shown in Fig. 1.

In this scheme compact sets $\mathbf{X}_i \subset R^n$ are mapped into elements $y_i \in R^m; (i = 1, 2, \ldots)$ in the output space by the decision function $\mathbf{P}$. The elements of $\mathbf{X}_i$ denote the input patterns corresponding to class y_i. In dynamical systems the operator $\mathbf{P}$ of a given plant is defined by the input–output pairs $\{x(t), y(t)\},\ t \in [0, T]$. The objective of identification is to compute $\widehat{\mathbf{P}}$ so that

$$\|\hat{y} - y\| = \|\widehat{\mathbf{P}}(x) - \mathbf{P}(x)\| \leqslant \varepsilon, \quad x \in \mathrm{X} \tag{1}$$

where ε is some desired small value and $\|.\|$ denotes the Euclidean norm on the output space. In Fig. 1 $\widehat{\mathbf{P}}(x) = \hat{y}, \mathbf{P}(x) = y$ and e denote the output of the model, the output of the system and the error between the two respectively. In this case,

$$e = y - \hat{y} \tag{2}$$

The input x is assumed as an uniformly bounded function of time. In this paper single-input single-output (SISO) and multi-input multi-output (MIMO) plants of four different nonlinear models are considered. These plants are described by the nonlinear difference equations given in (3)–(6).

Model 1

$$y(k+1) = \sum_{i=0}^{n-1} \alpha_i y(k-i) + g[x(k), x(k-1), \ldots, x(k-m+1)] \tag{3}$$

Model 2

$$y(k+1) = f[y(k),\ y(k-1), \ldots, y(k-n+1)] + \sum_{i=0}^{m-1} \beta_i x(k-i) \tag{4}$$

Model 3

$$y(k+1) = f[y(k), y(k-1), \ldots, y(k-n+1)] + g[x(k),\ x(k-1), \ldots, x(k-m+1)] \tag{5}$$

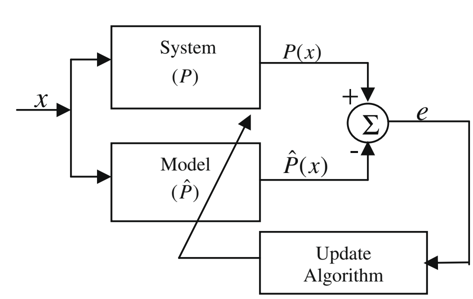

Fig. 1. Identification scheme of a dynamic system.