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Combined fitness function based particle swarm optimization algorithm for system identification

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ABSTRACT

An improved particle swarm optimization (PSO) algorithm, called combined fitness function based particle swarm optimization algorithm is presented in this investigation. PSO algorithm originated from bird flocking models and is effective in solving system identification problems. However in the identification process, single measure like the squared error between the measured values and the modeled ones may be not a sufficient criterion. The improved PSO algorithm adopts a combined fitness function to solve this problem. Mean Square Error (MSE) and Grey Absolute Relational Grade (GARG) are employed as evaluation measures, and entropy method is used to determine the relative weights of the two measures. Numerical simulations and experiments are carried out to evaluate the performance of the improved PSO. Consistent results demonstrate that combined fitness function based PSO algorithm is feasible and efficient for system identification, and can achieve better performance over conventional PSO algorithm.

1. Introduction

System identification is the field of approximating dynamic system models using experimental data (Saleem, Taha, Tutunji, & Al-Qaisia, 2015). Its basic idea is to compare the time dependent responses of the actual system and identified model based on a performance function giving a measure of how well the model response fits the system response (Alfi & Fateh, 2010). Much effort has been devoted to develop computational methods for system identification problem over the years. Various techniques, such as the recursive least square method (Ding, Wang, & Ding, 2015), recursive prediction error approach (Wigren, 1993) and maximum likelihood method (Hagenblad & Ljung, 2000), have been applied for building accurate mathematical models of dynamic systems successfully. Despite their success in system identification, they have some fundamental problems, including their dependence on unrealistic assumptions such as unimodal performance landscapes and differentiability of the performance function, and trapping in local minima (Alfi & Fateh, 2010). Recently evolutionary algorithms (EAs) which impose less restriction have attracted researchers' attention (Tang, Qiao, & Guan, 2010). EAs incorporate random search and selection principle to achieve the global optimal solution (Panda, Pradhan, & Majhi, 2011). Several evolutionary computation techniques have been used in research areas such as parameter estimation of linear and nonlinear dynamic processes (de Azevedo Dantas, Maitelli, da Silva Linhares, & de Araujo, 2015). Particle swarm optimization (PSO) is a frequently used evolutionary algorithm. It was firstly introduced by Kennedy and Eberhart (Eberhart & Kennedy, 1995; Kennedy & Eberhart, 1995), and can be easily programmed with basic mathematical and logic operation (Tungadio, Numbi, Siti, & Jimoh, 2015). In many identification applications, PSO has been successfully utilized, such as infinite impulse response (IIR) system identification problem (Upadhyay, Kar, Mandal, & Ghoshal, 2014), power system state estimation (Tungadio et al., 2015), Wiener model identification (Tang et al., 2010), and ship motion model identification (Chen, Song, & Chen, 2010).

Since the conception of the PSO, researchers have attempted various ways to analyze and improve PSO algorithm. Wang and Yeh (2014) proposed a modified PSO which introduces the idea of sub-particles, a particular coding principle, and a modified operation procedure of particles to the update rules to regulate the search processes for a particle swarm. By analyzing the dynamic characteristics of PSO through a large number of experiments, Zhang, Ma, Wei, and Liang (2014) constructed a relationship between the dynamic process of PSO and the transition process of a control system. To estimate the parameters of surge arrester models, Nafar, Gharehpetian, and Niknam (2011) proposed a mod-

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ified particle swarm optimization which combines Ant Colony Optimization and PSO algorithm. The suggested algorithm selects optimum parameters for the arrester model by minimizing the error among simulated peak residual voltage values given by the manufacturer. Some other studies on improvements of PSO may be found in (Gosciniak, 2015; Wu, Wu, Hu, & Wu, 2013; Yang, Liu, & Yang, 2013; Yu, Ren, Du, & Shi, 2012). Galewski (2014) pointed out that an important part of the PSO algorithm tuning is a proper choice of fitness function. Therefore, in this investigation for further evaluation of the true level of fitness of a candidate particle, we'll combine two objective functions with entropy method. The two functions evaluate the particle fitness from different perspectives. Entropy method can ensure effective combination of the two functions. In the iterative process, if one has trouble in determining which particle is better, the other one would play a dominant role. In this way, the combined fitness function could help PSO algorithm enhance global optimization capability.

The remainder of this paper is organized as follows. In Section 2, the idea of system identification with PSO algorithm is described. Section 3 analyzes the problem of fitness function with the squared error, and an improved PSO algorithm with combined fitness function is presented. In Section 4, combined fitness function based PSO algorithm is validated with numerical simulations. Subsequently, some experiments are carried out in Section 5 and the experimental findings are discussed. Finally, Section 6 concludes this paper.

2. Particle swarm optimization based system identification

2.1. Preliminaries of PSO

Particle swarm optimization algorithm is motivated by the social behavior of organisms such as bird flocking and fish schooling (Tang et al., 2010). The PSO algorithm maintains a swarm of particles representing candidate solutions for a given optimization problem (Zhang et al., 2014). Particles start flying from the initial positions through the search space with velocities. The velocity of each particle is dynamically adjusted according to its own flying experience and its companions' flying experiences, and the performance of each particle position is evaluated by a fitness function. During the flight, the best previous experience for each particle is stored in its memory and called the personal best (Pbest), the best previous position among all particles is called the global best (Gbest) (Li et al., 2014; Marion, Scorretti, Siauve, Raulet, & Krähenbühl, 2008; Tungadio et al., 2015).

Let $X_i = (x_{i1}, x_{i2}, \ldots, x_{iN})$ be the position of the i th particle in a N dimensional search space. Similarly, the velocity V_i, the personal best X_i^{Pbest} of each particle and the global best X^{Gbest} are represented as $V_i = (v_{i1}, v_{i2}, \ldots, v_{iN})$, $X_i^{\text{Pbest}} = (x_{i1}^{\text{Pbest}}, x_{i2}^{\text{Pbest}}, \ldots, x_{iN}^{\text{Pbest}})$, and $X^{\text{Gbest}} = (x_1^{\text{Gbest}}, x_2^{\text{Gbest}}, \ldots, x_N^{\text{Gbest}})$ respectively. The particles are manipulated according to the following equations (Al-Duwaish, 2011; Li et al., 2014)

$$\begin{aligned} V_i(k+1) &= wV_i(k) + c_1 r_1 \left(X_i^{\text{Pbest}}(k) - X_i(k)\right) \\ &\quad + c_2 r_2 \left(X^{\text{Gbest}}(k) - X_i(k)\right), \end{aligned} \tag{1}$$

$$X_i(k+1) = X_i(k) + V_i(k+1), \tag{2}$$

where acceleration coefficients c_1, c_2 are positive constant parameters with the constraint $c_1 + c_2 \leqslant 4$, they control the maximum step size; r_1, r_2 are uniformly distributed random variables in the range $[0, 1]$; w is the inertia weight and controls the impact of the previous velocity on its current one, it is suggested to be chosen from the interval $[w_{\min}, w_{\max}]$ according to the following equation,

$$w(j) = w_{\max} - \frac{j}{iter_{\max}}(w_{\max} - w_{\min}), \tag{3}$$

where j is the current iteration generation, $iter_{\max}$ is the maximum iteration times, $w_{\min}$ and $w_{\max}$ are the minimum inertia weight and maximum inertia weight, respectively.

2.2. Schematic for system identification

The main task of system identification is to search iteratively for the parameters of the modeled system such that the input–output relationship matches closely to that of the actual system (Upadhyay et al., 2014). The basic block diagram for system identification is shown in Fig. 1. Most nonlinear systems are also recursive in nature; thus, models for real world systems are better represented as IIR systems (Luitel & Venayagamoorthy, 2010). An IIR system can be represented by the following transfer function (Luitel & Venayagamoorthy, 2010; Upadhyay et al., 2014):

$$H(z) = \frac{\sum_{k=0}^{m} b_k z^{-k}}{1 + \sum_{k=1}^{n} a_k z^{-k}}, \tag{4}$$

where m and n are the numbers of numerator and denominator coefficients, a_k and b_k are the pole and zero parameters which are to be identified in the work.

System input $x(k)$ is given to both the unknown system to be identified and the modeled system. The output $y'(k)$ mixed with a noise signal gives the final output $y(k)$ to the actual system. On the other hand, the modeled system has an output of $\hat{y}(k)$ for the same input. The difference $e(k)$ between the two output signals is used by the identifier to adjust the parameters. Many techniques for the identifier have been studied. For example, Sun and Liu (2013) proposed a method named Maximum likelihood-adaptive particle swarm optimization, and this method is demonstrated to be better than recursive least-squares (RLS) algorithm both in terms of convergence speed and accuracy. Ursem and Vadstrup (2004) compared the performance of eight stochastic optimization algorithms on identification of two induction motors. The eight algorithms represent four main groups of algorithms: local search (LS), evolution strategies (ESs), generational evolutionary algorithms (EAs), and particle swarm optimizers (PSOs). From their experiments, they drew one conclusion that population-based stochastic optimization techniques (ESs, EAs, and PSOs) significantly outperformed the local search algorithms. Therefore in this study, we would employ PSO algorithm to finish the identification.

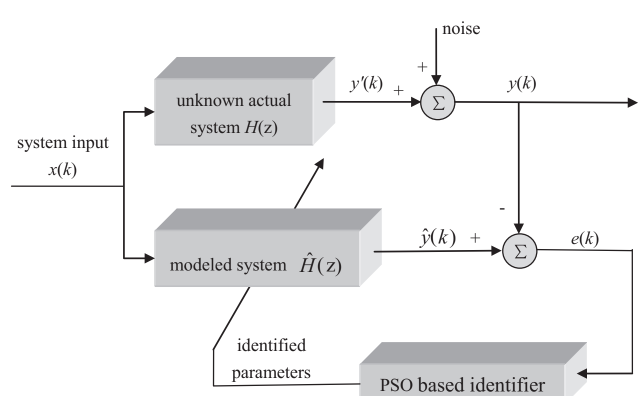

Fig. 1. Block diagram for system identification.