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A diversified shuffled frog leaping: An application for parameter identification

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ABSTRACT

This paper proposes a modified shuffled frog leaping (SFL) for solving parameter identification problems. The SFL divides a population into several memeplexes and then improves each memeplex in an evolutionary process. One of the main drawbacks of SFL is a limitation in its number and variety of search moves. This modification concentrates to diversify search moves of SFL by inserting a differential operator into evolutionary process of SFL. Experiments are performed on parameter identification problems and the obtained results are compared with some other algorithms reported in the literature. Practical experiences show that the proposed algorithm is very effective and robust so that it produces similar and promising results over repeated runs. The obtained results demonstrate a significantly better performance of our proposed algorithm than other revolutionary algorithms reported in the literature.

1. Introduction

One of classical problems in control engineering is system identification. The system identification is performed in four stages: (i) Data acquisition which is the process of sampling signals that measure real world physical phenomenon. (ii) Model structure selection which is based upon an understanding of both the identification procedure, and the system to be identified or in the other words understanding of the physical systems. (iii) Parameter estimation which value of some parameters related to be chose model affects the distribution of the measured data. An estimator attempts to approximate the unknown parameters using the measurements. (iv) Model validity tests which state that how well the model represents the patterns seen in real-world applications and how well the data used reflect current experiment and practice. In the current research we focus upon parameter estimation stage. So the model structure is definite and the employed approach must estimate parameters of model from a set of possibly noisy input–output data.

Historically, parameters estimation has been primarily treated by the least-squares method. It has been successfully used to estimate the parameters in static and dynamical systems, respectively. But, the least-squares method is only suitable for the model structure of system having the property of being linear in the parameters. Once the form of model structure is not linear in the parameters, this approach may be invalid. Heuristic algorithms especially with stochastic search techniques seem to be a more hopeful approach and provide a powerful means to solve this problem. They seem to be a promising alternative to traditional techniques, since (i) the objective functions gradient is not required, (ii) they are not sensitive to starting point, and (iii) they usually do not get stuck into so called local optima [1]. Recently, Evolutionary algorithms (EAs)have

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attracted wide research attention. EAs are a broad class of stochastic optimization algorithms inspired by biology and, in particular, by those biological processes that allow populations of organisms to adapt to their surrounding environments: genetic inheritance and survival of the fittest. EAs have a prominent advantage over other types of numerical methods. They only require information about the objective function itself, which can be either explicit or implicit. Other accessory properties such as differentiability or continuity are not necessary. As such, they are more flexible in dealing with a wide spectrum of problems [2]. One of recently proposed EAs introduced by Eusuff and Lansey [3] is shuffled frog leaping (SFL) algorithm. It was inspired from social researching of frogs for food resources. The SFL was derived by combining the concepts of shuffled complex evolution (SCE) and particle swarm optimization (PSO) algorithms. The SFL has been applied on a wide variety of optimization problems such as design of watermarking schemes [4], localization of wireless sensor network [5], job shop scheduling problems [6], unit commitment problem [7], project scheduling problem [8] and distribution feeder reconfiguration problem [9]. The SFL has excellent performance, but suffers from shortcomings of easily falling into local minima, slow convergence in later stage of evolution, poor calculation accuracy [5]. To overcome these shortcomings, a variety of concepts have been proposed in the literature. A particle sharing based particle swarm frog leaping hybrid optimization algorithm was proposed by Hui and Jia [10]. They combined the good capability of exploration in the PSO and the strong ability of exploitation in the SFL to overcome the shortcomings of easily falling into local minima and premature convergence. Zheng et al. [11] proposed a SFL with memory function which contained a memory of past experiences and initial learning function. The frog could record the leaping distance in the last update, and used it to update the leaping distance of this time. Tang-Huai et al. [5] used a strategy to improve the targeted learning of frog group and also to expand the diversity of frog group learning. Their proposed algorithm introduced a new update learning strategy in the update process, making the poor frog learned not only from the best frog of its own ethnic group, but also learned from the best frog of the population, and at the same time added a diversity factor in the update learning strategy. Li et al. [12] concentrated on improving the leaping rule of SFL performed by properly extending the leaping step size and adding a leaping inertia component to account for social behavior. To further improve the local search ability of their proposed algorithm and speed up convergence, they occasionally introduced extremal optimization, which had an excellent local exploration capability, in the local exploration process of the algorithm. The idea used in Niknam and Azad-farsani [13] was a new frog leaping rule to obtain a better local exploration of the SFL. They also proposed a hybrid EA which was the combination of self-adaptive PSO and modified SFL. Fang and Wang [14] to enhance the exploitation ability performed a combined local search including permutation-based local search and forward–backward improvement in each memeplex of SFL. Also basing on some theoretical analysis, speed-up evaluation methods were proposed to improve the efficiency of the SFL.

In the current research, we insert a new differential operator in evolutionary process of the SFL to diversify its search moves and to prevent a premature loss of the genotypic diversity. The added operator also provides an overall and deep search of space. So it can overcome the shortcomings of premature convergence where the population easily falls into some local optimum of a multimodal objective function and the population loses its diversity.

The rest of the paper is organized as follows. In the next section, the SFL algorithm is briefly described. In Section 3, the utilized strategy to improve the SFL is presented. The simulation results are presented and analyzed in Section 4. Section 5 concludes the paper.

2. The SFL

The SFL has been inspired by the memetic evolution of a set of frogs when researching for the location of food. Partitioning of frogs into several groups called memeplexes is an effective strategy particularly whenever the resource is unpredictably distributed in patches. Every memplex involves a number of frogs with the same structure but different adaptabilities. On the other part, shuffling process causes participating of every frog in previous experience of all other frogs during the search for food. The SFL investigated by combining the ideas used in the SCE algorithm and PSO to design an improved meta-heuristic to solve optimization problems. The SFL is a combination of deterministic and random approaches. The deterministic strategy allows the algorithm to use response surface information effectively to guide the heuristic search as in the PSO. The random elements ensure the flexibility and robustness of the search pattern [15].

The SFL includes three main stages: partitioning, local search and shuffling. In the SFL, candidate solutions initialize randomly in search space and then members of population are sorted as a decreasing order according to their fitness. Then population is partitioned into several parallel subsets. The different memeplexes perform a local search independently using an evolutionary process to evolve their quality for a defined maximum number of iterations. Then all memeplexes shuffle together and the termination criteria are checked that if are not met, the partitioning, local search and shuffling process are continued. General framework of SFL and a flowchart of its structure are shown in Figs. 1 and 2, respectively. According to the evolutionary process of SFL, the worst frog of each memeplex updates its position according to the position of the best frog of its memeplex or the best frog found so far or randomly.

To generate a new frog in every memeplex, firstly the SFL applies Eqs. (1) and (2) between x_b and x_w to produce x_n (*Step 3.4* in Fig. 1).

$$\Delta x_w = \lambda(x_b - x_w), \quad -\Delta x_{w\,\max} \leqslant \Delta x_w \leqslant \Delta x_{w\,\max} \tag{1}$$

$$x_n = x_w + \Delta x_w \tag{2}$$