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A novel phase performance evaluation method for particle swarm optimization algorithms using velocity-based state estimation

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ABSTRACT

The searching process of particle swarm optimizations (PSO) includes four states: *exploration*, *exploitation*, *convergence* and *jump-out*. Performance information of each state is essential to learn the characteristics of different algorithms as well as to improve their performances. To this end, this paper discusses a novel performance evaluation method of each phase in PSOs. Firstly, we propose a velocity-based state estimation (VSE) method, which can estimate the real-time state of PSO variants with less computation. Subsequently, we provide a phase performance evaluation based on VSE, which includes phase identification, two kinds of phase performance indicators and ranking method. Finally, we design hybrid algorithm experiments, to compare phase performance of six main PSO algorithms, and the phase replacement experiments is used to verify the experimental results.

1. Introduction

Since particle swarm optimization (PSO) algorithm has been proposed in 1995 [1], it has become an efficient method for searching approximate optimal solution due to its simplicity compared with other evolutionary algorithms [2], e.g. genetic algorithm(GA) [3], differential evolution (DE) [4] and biogeography based optimization (BBO) [5]. PSO algorithm inspired from bird foraging has become a new method, which relies on a simple velocity update rules to make the particles move. It has better ability to find the global optimum solution [6] with good performance in both unimodal and multi-modal problems [7].

However, the standard PSO algorithm is easy to premature and fall into local optimal. In order to overcome this shortcoming, many scholars have studied various mechanisms to improve the PSO algorithms, which includes the parameter adaption [8,9], topology variations [10], learning schemes [11,12] and sub-swarms [13–15]. PSO is widely used in the related fields of computational science and applied mathematics, such as artificial neural network training [16,17], business optimization [18].

In the field of optimization, numerous variants of PSO algorithms have been proposed and evaluation between different algorithms has become a hot research direction. Researchers test algorithms on benchmark functions and compare the results to learn which algorithms have better offline performances [19,20]. However, this information is not sufficient to help us improve the algorithms or choose algorithm to apply in the hybrid algorithm, and more detailed performance data is needed.

Different with other evolutionary algorithms, PSO usually experiences the phases of exploration, exploitation and convergence during the optimization process [21], optimal parameters and strategies of each phase of PSO is different. For example, PSO needs a large inertia weight w and a small global learning factor c_2 for wide exploration and diversity of particles in the exploration phase [22]. Similarly, different PSO variants may be more suitable for certain phase. Therefore, the purpose of this paper is to propose an evaluation method that contemplates the performance in every phases to provide detail information about PSO variants.

In order to distinguish different phases of PSOs during the optimization process, velocity-based state estimation (VSE) is firstly proposed in this paper, which can estimate the evolutionary state of particles population by the velocity. Then, phase identification method is presented based on VSE. Meanwhile, two phase evaluation indicators and ranking method are introduced to evaluate the performance in certain phase. The phase evaluation method reveals the phase performance and characteristics of the algorithm, which can be verified by the phase replacement experiments. The rest of the paper is organized as follows. Section 2 briefly describes the related work. Section 3 presents the VSE approach in detail. Section 4 proposes the phase identification, two phase evaluation indicators and ranking method. Section 5 presents phase evaluation experiment of six PSO algorithms, phase replacement experiments

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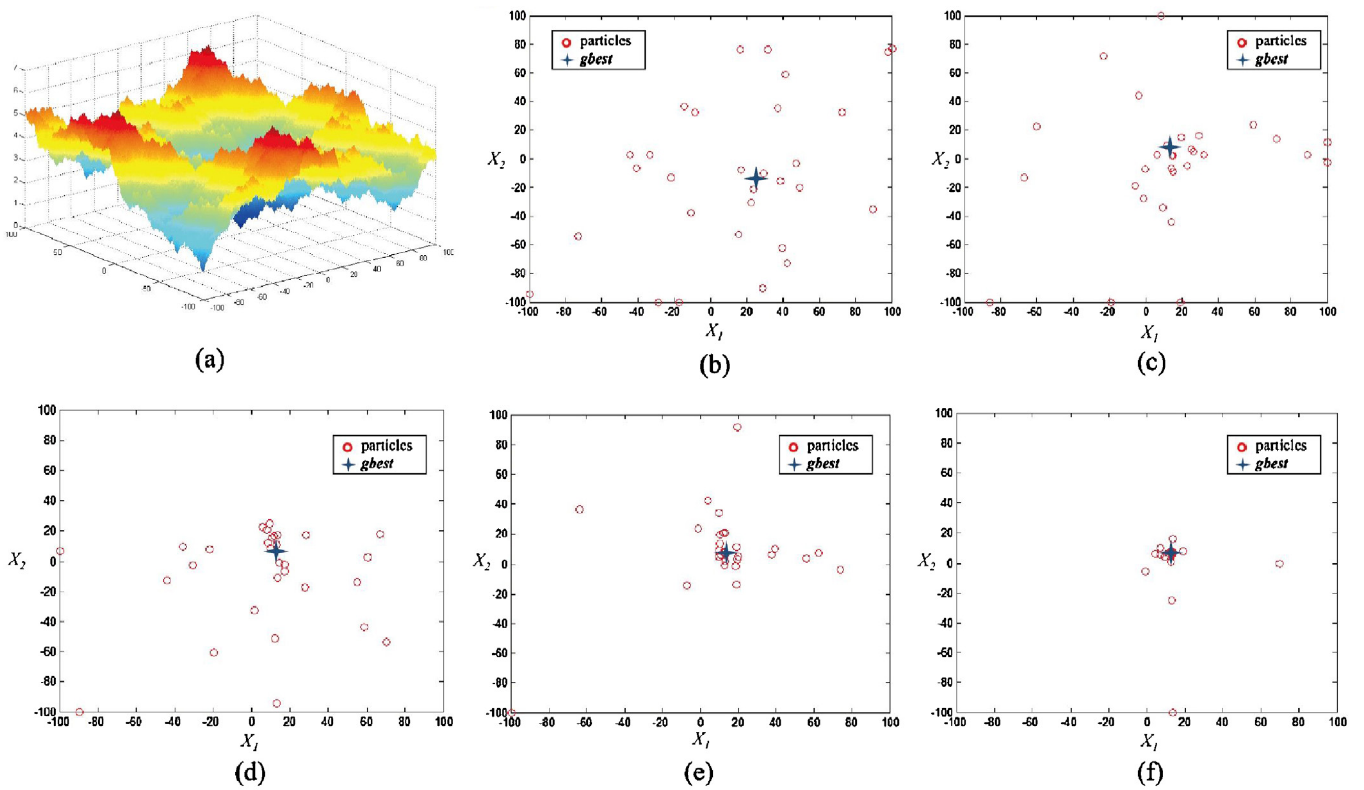

Fig. 1. The change of population distribution at different v_{all}: (a) 3-D map for 2-D Weierstrass function, (b) Population distribution when v_{all}/V_{ini} = 0.9, (c) Distribution when v_{all}/V_{ini} = 0.7, (d) Distribution when v_{all}/V_{ini} = 0.5, (e) Distribution when v_{all}/V_{ini} = 0.3, (f) Distribution when v_{all}/V_{ini} = 0.1.

and discussions. Finally, Section 6 presents the conclusions and suggests some directions of future work.

2. Related work

2.1. PSO framework

In PSO algorithm, each particle is represented as a potential solution, and particles achieve global optimum by moving their position in a D-dimension search space. The velocity $\boldsymbol{v_i}$ and the position $\boldsymbol{x_i}$ are updated as follows:

$$\boldsymbol{v_i}(t+1) = \boldsymbol{v_i}(t) + c_1 r_1 (\boldsymbol{p_i} - \boldsymbol{x_i}) + c_2 r_2 (\boldsymbol{g} - \boldsymbol{x_i}) \quad (1)$$

$$\boldsymbol{x_i}(t+1) = \boldsymbol{x_i}(t) + \boldsymbol{v_i}(t) \quad (2)$$

where $\boldsymbol{x_i} = (x_{i1}, x_{i2}, \ldots, x_{iD})$ is the position of the ith particle, $\boldsymbol{v_i} = (v_{i1}, v_{i2}, \ldots, v_{iD})$ is the velocity of particle i, t represents the generation number, c_1 and c_2 are local and global learning factors respectively, r_1, r_2 are random numbers between [0,1], $\boldsymbol{p_i}$(also express as $\boldsymbol{pbest_i}$) stands as the previous best position for the particle i, $\boldsymbol{g}$ (also express as $\boldsymbol{gbest}$) is the global best position found so far in the entire swarm. The particle position is updeted by Eq. (2).

Added with an inertia weight factor w, the algorithm can have a better control over the search scope, and can achieve better results in the application of certain issues [23], and the particle velocity is adjusted to:

$$\boldsymbol{v_i}(t+1) = w \cdot \boldsymbol{v_i}(t) + c_1 r_1 (\boldsymbol{p_i} - \boldsymbol{x_i}) + c_2 r_2 (\boldsymbol{g} - \boldsymbol{x_i}) \quad (3)$$

2.2. Performance evaluation methods

There are two common methods to evaluate algorithm performance so far. One is to test the results of algorithm on benchmark functions until algorithm reach the prepared maximum iteration, and then to learn offline performance of algorithms on certain functions. For example, N. Hansen el. tested 11 kinds of evolutionary algorithm on CEC benchmark functions [24], A. Al-Dujaili el. performed experiments about eight kinds of PSO variants on benchmark functions for performance comparison [7]. The other one is to combine different PSO modifications to find better PSO variants. For example, M. Jakubcováel. combined three distributions of the population and nine types of inertia weight to 27 PSO variants [25]. B. Qi and F. Shen formed five different algorithms with combination of different factors c_1 and c_2 [26].

2.3. Evolutionary state estimation

Evolutionary State Estimation (ESE) is a method used to estimate the state of evolutionary algorithms in real time. It is important because the requirement of each state is different.

In PSO algorithm, a successful search process usually consists of the following states [21]. At first, particles search in the problem space in large scale, and then update the global best particle with mutual comparison of fitness value, which is called the state of *exploration*. After finding a relatively stable global best position, particles gradually gathered to the position for local search, and we call it *exploitation*. If global best position is very close to the global optimal solution, particles will continue to search in the region and converge to the global optimum, and this state is called *convergence*. Otherwise, if particles fall into a local optimal region, they may find better area with the random perturbation, to jump out of the local optimum to search the new region, and this state is called *jump-out*.

J. Zhang et al. firstly propose ESE in the GA [27]. Subsequently, Z.H. Zhan et al. applied it in PSO due to PSO and GA are both evolutionary algorithm [28]. This method is to cluster all particles into three groups by K-means clustering algorithm according to Euclidean distance, and estimate the evolutionary state by judging