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Enhanced particle swarm optimization based on principal component analysis and line search

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ABSTRACT

Particle swarm optimization (PSO) guides its search direction by a linear learning strategy, in which each particle updates its velocity through a linear combination among its present status, historical best experience and the swarm best experience. The current position of each particle can be seen as a velocity accumulator. Such a storage strategy is easy to achieve, however, it is inefficient when searching in a complex space and has a great restriction on the achieved heuristic information for the promising solutions. Therefore, a new PSO searching mechanism (PCA-PSO) is proposed based on principal component analysis (PCA) and Line Search (LS), in which PCA is mainly used to efficiently mine population information for the promising principal component directions and then LS strategy is utilized on them. PCA-PSO can inherit most of the velocity information of all the particles to guide them to the most promising directions, which have great difference in learning mechanism with usual PSOs. Experimental results and extensive comparisons with hybrid PSOs, pPSA, PCPSO, CLPSO, GL-25, and CoDE show that PCA-PSO consistently and significantly outperforms some PSO variants and is competitive for other state-of-the-art algorithms.

1. Introduction

Nature inspired optimization algorithms, such as genetic algorithm (GA) [1], artificial bee colony algorithm (ABC) [2], differential evolution (DE) [3], ant colony optimization [4] and particle swarm optimization algorithm (PSO) [5], harmony search algorithm [6], have aroused wide research interests. All of them are inspired by the natural/social swarm behaviors. High dimensional optimization problems solving and engineering applications show that these biological-inspired optimization algorithms are competitive and well adapted for a wide research and application [7].

The outstanding feature of PSO is its learning mechanism which distinguishes it from other biological-inspired optimization techniques. PSO updates each particle's velocity by three items—one inertia term that provides the particle with a necessary momentum, one self cognitive term that reflects the personal thinking of the particle itself and one social cognitive term that indicates how the particles are stochastically drawn towards the global best position found by the entire swarm. In 1995, Kennedy and Eberhart [8] put forward this learning strategy by using a linear combination of these three terms and storing the learning experience in the current position. Many improved learning strategies have been proposed since its emergence. Liang et al. [9] proposed a novel learning strategy whereby all other particles' historical best information is used to update a particle's velocity. This strategy enables the diversity of the swarm to be preserved to discourage premature

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convergence and achieves very competitive performance for multimodal functions. Wang et al. [10] employed a generalized opposition-based learning (GOBL) and Cauchy mutation to provide a faster convergence and help particles escape from the local optima. Cho et al. [11] presented another novel multi-modal algorithm by using some deterministic samplings to generate new particles for finding multiple local optima in objective function surfaces. Nickabadi et al. [12] proposed a new adaptive inertia weight by using the success rate of the swarm as its feedback parameter to ascertain the particles' situation in the search space. Zhan et al. [13] applied a novel orthogonal learning strategy to improve performance of PSO algorithm (OLPSO). Hybridized with immune optimization strategy, Zhao et al. [14] proposed a particle swarm optimization for Quality of Service (QoS)-driven web service composition with global QoS constraints. It is well known that all the learning experience collected from various learning strategies of all the PSO variants is stored in the current positions. However, even more important questions that how much extent storage strategies are helpful do not arouse much more interests until now. The learning experience acquired by the linear combination with three terms is traditionally believed to be inherited among particles from a parent particle to an offspring solely. However, the inherited experience of the offspring particle is not abundant via a traditional storing mechanism.

In 2005, Voss tried to apply PCA technology [15] to PSO algorithm (named as PCPSO [14]) by some means. The inspiration of PCPSO is derived from a methodology known as the Lagrange point of view [17–19] for creating and flying in a dynamic coordinate system with the particles. A new approach using kernel principal component analysis (KPCA) [20] and multi-class support vector machine (SVM) for improving the classification of power quality disturbance signals is presented. The KPCA is utilized to reduce the feature dimension by projecting the multiresolution analysis features into the KPCA spaces and then compute kernel principal components. PSO is applied to optimize the KPCA and SVM parameters. Because the absorbing bound-handling approach may paralyze PSO when it is applied to high-dimensional and complex problems, Chu et al. [21] introduced principal components analysis into PSO to remedy the problem caused by the absorbing bound-handling approach. Inspired by Hamiltonian Monte Carlo (HMC) method, Kuznetsova et al. [22] proposed PCA-based Stochastic Optimization (PCA-SO) algorithm. They showed the benefits of PCA-SO being integrated in three different stochastic optimization/sampling methods, namely random sampling, simulated annealing and particle filtering.

In this paper, a multivariate statistical method of principal component analysis (PCA) [16], which can reduce the dimension of the handled multivariate data to some extent, is introduced to velocity updating operations of PSO. The algorithm is denoted as PCA-PSO which guides particles to more promising searching areas by a new velocity storage strategy. It extracts the velocity information (experience) as much as possible from all the parent particles and inherits to offspring particles. So PCA-PSO provides a novel search mechanism and a new approach to get higher quality solutions in the high dimensional spaces by storing the historical experience and global best experience of all the particles.

The rest of the paper is organized as follows. PSO is introduced in Section 2. The statistical method of principal component analysis and how it works are proposed in Section 3 and 4 introduces the line search technology. The algorithm PCA-PSO, i.e. why and how to combine PCA with PSO are presented in Section 5. In Section 6, extensive experimental comparisons with hybrid PSOs, pPSA, PCPSO and other state-of-the-art optimization algorithms are conducted to verify the efficacy and efficiency of PCA-PSO. Finally, conclusions and possible future research are given in Section 7.

2. Particle swarm optimization

Particle swarm optimization [8] is an optimization technique based on the cooperation and competition among individuals to complete the search of the optimal solution in an n-dimensional space. There is a swarm of particles and each individual has a fitness value which is decided by the objective function. During the swarm evolution, each particle has a velocity vector $V_i = (v_{i1}, v_{i2}, \ldots, v_{in})$ and a position vector $X_i = (x_{i1}, x_{i2}, \ldots x_{in})$ to guide itself to a potential optimal position, where i is a positive integer indexing the particle in the swarm and n is the dimension size of the search space. Moreover, particle tracks two extremes to update itself. One is its personal historical best position P_i and the other is the best position found by the entire swarm, which is denoted as P_g. The velocity V_i and the position X_i are randomly initialized in the search space and they are updated with the following formulas under the guidance of P_i and P_g:

$$v_{id}(k+1) = \omega v_{id}(k) + c_1 r_1 (p_{id}(k) - x_{id}(k)) + c_2 r_2 (p_{gd}(k) - x_{id}(k)) \tag{1}$$

$$x_{id}(k+1) = x_{id}(k) + v_{id}(k) \tag{2}$$

where $d \in \{1, 2, \ldots, n\}$, ω is the inertia weight, coefficients c_1 and c_2 are cognitive and social weights and r_1, r_2 are two uniform random numbers within the range of $[0, 1]$.

In this paper, a PSO variant with local ring topology neighborhood is used to update the velocity as follows.

$$v_{id}(k+1) = \omega v_{id}(k) + c_1 r_1 (p_{id}(k) - x_{id}(k)) + c_2 r_2 (p_{r(i)d}(k) - x_{id}(k)) \tag{3}$$

where $p_{r(i)d}(t)$ is the best historical position among its NR neighbors.