A New Cooperative PSO Approach with Landscape Estimation, Dimension Partition, and Velocity Control

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ABSTRACT

Particle swarm optimization (PSO) has been proposed as an alternative to traditional evolutionary algorithms. Yet, more efficient strategies are still needed to control the trade-off between exploitation and exploration in the search process for solving complex tasks with high dimensional and multimodal objective functions. In this work, the authors propose a new PSO approach to overcome the search difficulties. Their approach first predicts the landscape type of a function for initial search settings, and then focuses on two search strategies for multimodal functions. One is a two-swarm cooperative strategy that controls search region and integrates partial and full dimension PSO search. The other strategy is to control the velocity of the particles in an adaptive way, according to how they move in the space. To evaluate the proposed approach, extensive experiments have been conducted and comparisons to several popular PSO variants have been made. Our experiments prove that the proposed approach can have better performance than others in most of the test cases.

Keywords: Adaptive Velocity Control, Cooperative Strategy, Dimension Partition, Multimodal Function, Particle Swarm Optimization, Swarm Intelligence

1. INTRODUCTION

Evolutionary algorithms (EAs) are population-based optimization approaches and are regarded a collective learning process within a population of individuals in which each individual represents a search point in the space of potential solutions for a given problem. They evaluate many solutions simultaneously in the search space, and are likely to find a global solution for a given problem. A new population-based optimization technique, particle swarm optimi-
zation (PSO, Kennedy & Eberhart, 2001), has been proposed as an alternative to traditional EAs. It attempts to mimic the goal-seeking behavior of biological swarms. In PSO, a possible solution of the optimization problems is represented as a particle and the algorithm operates in an iterative manner. Unlike traditional EAs, particles in PSO do not perform the operator of genetic re-combination between particles, but they work individually with social behavior in swarms. PSO has some attractive characteristics. In particular, it has memories, so that knowledge of good solutions can be retained by all particles (solutions). This method has been successfully used to solve many discontinuous and complex problems with good results (Grimaccia, Mussetta, & Zich, 2006; Poli, 2008; Lee & Hsiao, 2011).

As can be observed, when an application task involves many parameters and the parameter dimension increases to match the increase in task complexity, the solution space grows exponentially. Consequently, the search becomes more and more difficult. Though different modified PSO algorithms have been proposed to give better solutions than the standard PSO does, their search quality declines soon for complex tasks with high dimensional and multimodal objective functions. In addition, as the distribution and density of these optimal solutions vary from function to function, it is difficult to design a general or universal strategy for all problem situations. This is mainly because of that PSO has a high convergence speed and this often results in the loss of diversity during the optimization process. The undesirable premature situation causes particles to get trapped in local optima and unable to gain the best solution. Therefore, an efficient strategy to well-control the trade-off between exploitation and exploration in the search process is still under investigation.

To overcome the search difficulties described above, in this work we propose a new PSO approach with three special features: landscape estimation, dimension partition, and adaptive velocity control. Landscape estimation is to predict the type of an unknown function (unimodal or multimodal) for initial search settings. Dimension partition is to control search direction and region. It involves a cooperative strategy that concurrently exploits the advantages of both single dimension and full dimension PSO algorithms. And adaptive velocity control means to dynamically regulate the flying speed of the particles, according to how they move in the space. To verify the proposed approach, extensive experimental runs have been conducted and comparisons between our approach and some famous PSO variants have been made. The results confirm the performance of our approach. They show that the proposed approach performs the best in most of the test functions, especially when the test functions are rotated and shifted to increase the complexity.

2. BACKGROUND AND RELATED WORK

Similar to other EAs, PSO is also a population-based technique. The basic PSO algorithm contains a set of particles and operates in an iterative manner. Each particle is characterized by its position and velocity, which moves in the search space. The position of each particle represents the potential solution and is evaluated by a predefined evaluation (fitness) function. During the iterative search process, each particle remembers its previous best position and the best position of any particle in the swarm. Then, the particle uses the above position information to modify its position and velocity, and continues its movement in the search space.

To enhance the performance of individuals, the main operator in the PSO is velocity updating for the particles, which combines the best position obtained by the swarm of particles and the best position reached by a certain particle during its flying history. It has the effect that the particles move towards the best position of the swarm. In the original PSO, the velocity and the position of a particle at time step $t+1$ are updated from those at time step $t$ by the following rules:
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