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A HYBRID PARTICLE SWARM OPTIMIZATION ALGORITHM BASED ON SPACE TRANSFORMATION SEARCH AND A MODIFIED VELOCITY MODEL

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Abstract. Particle Swarm Optimization (PSO) has shown its fast search speed in many complicated optimization and search problems. However, PSO often easily falls into local optima because the particles would quickly get closer to the best particle. Under these circumstances, the best particle could hardly be improved. This paper proposes a new hybrid PSO (HPSO) to solve this problem by combining space transformation search (STS) with a new modified velocity model. Experimental studies on 8 benchmark functions demonstrate that the HPSO holds good performance in solving both unimodal and multimodal functions optimization problems.

Key words. Space Transformation Search (STS), evolutionary algorithm, Particle Swarm Optimization (PSO), optimization.

1. Introduction

Particle swarm optimizer (PSO), which was firstly introduced by Kenedy and Eberhart in 1995[1,2], emulates the flocking behavior of birds to solve optimization problems. In PSO, each potential solution is considered as a particle. All particles have their own fitness values and velocities. These particles fly through the D-dimensional problem space by learning from the historical information of all the particles. A potential solution is represented by a particle that adjusts its position and velocity according to equation (1) and (2):

$$\upsilon_{id}^{(t+1)} = \omega\upsilon_{id}^{(t)} + c_1r_1(p_{id}^t - x_{id}^t) + c_2r_2(p_{gd}^t - x_{id}^t), \tag{1}$$

$$x_{id}^{(t+1)} = x_{id}^{(t)} + \nu_{id}^{(t+1)}, \tag{2}$$

where t is the time index, i is the particle index, and d is the dimension index. p_i is the individual best position. p_g is the known global best position. ω is the inertia weight described in [3]. c_1 and c_2 are the acceleration rates of the cognitive and social parts, respectively. r_1 and r_2 are random values different for each particle i as well as for each dimension d.The position of each particle is also updated in each iteration by adding the velocity vector to the position vector.

One problem found in the standard PSO is that it could easily fall into local optima in many optimization problems. One reason for PSO to converge to local optima is that particles in PSO can quickly converge to the best position once the best position has no change. When all particles become similar, there is a little hope to find a better position to replace the best position found so far. In this paper, a new hybrid PSO algorithm called HPSO is proposed. It avoids premature convergences and allows STS-PSO [4] to continue searching for the global optima

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by applying space transformation-based learning and to break away from local optimal with a new disturbing factor and a convergence monitor. Our HPSO has been tested on both unimodal and multi-modal function optimization problems. Comparison has been conducted among HPSO, standard PSO and STS-PSO. The rest of this paper is organized as follows: Section 2 presents the new HPSO algorithm. Section 3 describs the benchmark continuous optimization problems used in the experiments, and gives the experimental settings. Section 4 presents and discusses the experimental results. Finally, Section 5 concludes with a summary.

2. HPSO ALGORITHM

2.1. Space Transformation Search (STS). Many evolutionary optimization methods start with some initial solutions, called individuals, in an initial population, and try to improve them toward some optima solution(s). The process of searching terminates when some predefined conditions are satisfied. In some cases, the searching easily stagnates, when the population falls into local optima. If the stagnation takes places too early, the premature convergence of search is caused. Under these circumstances, the current search space hardly contains the global optimum. So it is difficult for the current population to achieve better solutions. However, Space transformation search, based on opposition learning method[5], originally introduced by Hui Wang [4], has proven to be an effective method to cope with lots of optimization problems. When evaluating a solution x to a given problem, we can guess the transformed solution of x to get a better solution x'. By doing this, the distance of x from optima solution can be reduced. For instance, if x is -10 and the optimum solution is 30, then the transformed solution is 40. But the distance of x' from the optimum solution is only 20. So the transformed solution x' is closer to the optimum solution. The new transformed solution X^* in the transformed space S can be calculated as follows:

$$x^* = k(a + b) - x, \tag{3}$$

where $x \in R$ within an interval of $[a, b]$ and k can be set as 0,0.5,1 or a random number within $[0, 1]$.

To be more specific, we put it in an optimization problem, Let $X = (x_1, x_2, x_n)$ be a solution in an n-dimensional space. Assume $f(X)$ is a fitness function which is used to evaluate the solution's fitness. According to the definition of the STS, $X^* = (x_1^*, x_2^*, x_n^*)$is the corresponding solution of X in the transformed search space. If $f(X^*)$ is better than $f(X)$, then update X with X^*; otherwise keep the current solution X. Hence, the current solution and its transformed solution are evaluated simultaneously in order to continue with the fitter one. The interval boundaries $[a_j(t), b_j(t)]$ is dynamically updated according to the size of current search space. The new dynamic STS model is defined by

$$X_{ij}^* = k[a_j(t) + b_j(t)] - X_{ij}, \tag{4}$$

$$a_j(t) = min(X_{ij}(t)), b_j(t) = max(X_{ij}(t)) \tag{5}$$

$$i = 1, 2, ..., PopSize, j = 1, 2, ...n$$

2.2. Modified Velocity Model. In the PSO, particles are attracted to their corresponding previous best particles $pbest_i$ and the global best particle $gbest$. With the movement of particles, particles are close to $pbest_i$ and $gbest$, and then $pbest_i - X_i$ and $gbest - X_i$ becomes small. According to the updating equation of velocity, the velocity of each particle become small. Once the $pbest_i$ or $gbest$ fall into local minima, all the particles will quickly converge to the positions of them.