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Adaptive mutation particle swarm algorithm with dynamic nonlinear changed inertia weight

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ABSTRACT

A novel adaptive mutation particle swarm optimization algorithm with dynamic nonlinear changed inertia weight (AMPSO) was presented to accelerate searching speed and avoid premature convergence, which are mainly adjusted by inertia weight and information mutation. Firstly, the average particle spacing (APS) is employed to describe the population diversity, the smaller the APS, the more concentrated population and the worse species diversity. Then, inertia weight of each particle is updated as dynamic nonlinear based on APS to achieve a self-adaptive adjustment of global search ability and local search capabilities. Finally, information mutation based on slowly varying function (SV) introduced into the updating formula of PSO algorithm to expand search space. The proposed algorithm was tested compared with conventional PSO algorithms by three benchmark functions. The experiments show that the AMPSO has a stronger global optimization capability and higher search efficiency.

1. Introduction

Particle swarm optimization (PSO) is one of the most widely used evolutionary algorithms inspired by the cooperative and competitive social behavior of animals [1,2], which has characteristics of swarm intelligence, intrinsic parallelism, iterative format simple and inexpensive computational [3–5]. Due to these advantages, PSO has been applied to many domains such as system identification [6], neural networks [7], and system control [8,9].

In spite of these advantages, PSO as a stochastic optimization technique can't avoid facing the problem of trapping in local optimum and slow convergence rate. Due to a few adjustable parameters such as population size, inertia weight and learning factor, PSO algorithm has been changed to solve the above problems by many researchers recently, especially inertia weight. Several classic improved PSO algorithms, such as PSO-linearly inertia weight (LPSO) [10], PSO-random inertia weight (RPSO) [11], PSO-fuzzy inertia weight (FPSO) [12] and PSO-nonlinear inertia weight (NPSO) [13], have been proposed. LDPSO is simple and intuitive, but particle swarm search process is a complicated nonlinear process, linear excessive method does not reflect the real search process. RPSO may produce relatively small inertia weight at early evolution stage, which can be better than the LPSO, but it was more applied in the dynamic system. FPSO needs expert knowledge based fuzzy rules, which is difficult to realize global optimization. NPSO has better optimization performance, but it needs to artificially set the range of decreasing inertia weight maximum and minimum that impact particle swarm to find the optimal value process.

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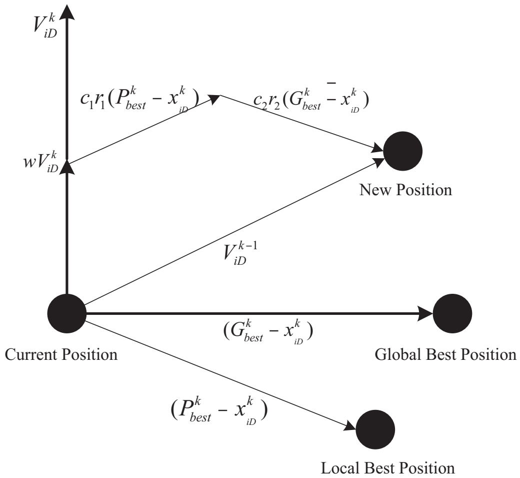

Fig. 1. particle movement schematic diagram.

At present these main methods to solve problems had obtained with a certain performance improvement, but convergence and scarce exploration are also the frequent problems in the application process [14,15].

In the background of the above analysis, a novel adaptive mutation particle swarm optimization algorithm with dynamic nonlinear changed inertia weight (AMPSO) is presented to improve searching speed and avoid premature convergence. The following sections of this paper are structured as follows. Section 2 introduces of the standard PSO. Section 3 proposes adaptive mutation particle swarm optimization algorithm with dynamic nonlinear changed inertia weight (AMPSO). Section 4 designs simulation experiment to compare with the conventional version of PSO algorithms. Section 5 describes algorithm description and flowchart. Finally, Section 6 discusses the conclusion.

2. The standard PSO algorithm

Standard PSO algorithm is simulating birds to fly foraging behavior, through collaboration between individuals to search for the optimal solution. In this algorithm, each optimization problem of potential solution is a bird in search space, called particle, each particle evaluates current position by the fitness function, and has a directional speed to decide its search path. In iteration, a particle tracks two extreme values to update them, the first is the individual extremum which the particle itself found, and the other is the global extremum which the whole population found. In D-Dimensional search space, there are m particles, position vector of each particle is denoted as $X_i^k = (x_{i1}^k, x_{i2}^k, \ldots x_{iD}^k)$, $i = 1,2,\ldots,m$, $k = 1,2,\ldots,K$, and velocity vector of each particle is $V_i^k = (v_{i1}^k, v_{i2}^k, \ldots v_{iD}^k)$. The optimal solution of individual particle is P_{best}^k, particle population optimal solution is G_{best}^k. The PSO algorithm according to the following formula changes the particle's position and velocity:

$$V_{iD}^{k+1} = wv_{iD}^k + c_1r_1(P_{best}^k - x_{iD}^k) + c_2r_2(G_{best}^k - x_{iD}^k) \quad (1)$$

$$x_{iD}^{k+1} = x_{iD}^k + V_{iD}^{k+1} \quad (2)$$

where w is the inertia weight, c_1 and c_2 are learning factors, r_1 and r_2 are the random number between 0 and 1. The first part of Eq. (1) represent particle initial velocity, the second part of Eq. (1) is the cognitive part, which expresses particle itself thinking and the third part of Eq. (1) is the social part, which expresses information sharing and cooperation [16–18]. The particle schematic diagram is shown as Fig. 1.

3. AMPSO

3.1. Population diversity measurement for premature judgment

A major problem in the application of standard PSO is the premature convergence, the reason for this problem is the emergence of excessive loss of population diversity. There are several measure indexes have been proposed including crowding distance [19] and average fitness [20], especially group fitness variance (GFA) [21,22]. GFA was proposed to evaluate the premature convergence phenomena, but it is only from the aspects of function value to reflect the overall distribution of particles, which cannot identify size of the distance between the individual. Therefore, the average particle spacing (APS)