Applied Soft Computing 13 (2013) 3853–3863

Contents lists available at SciVerse ScienceDirect

Applied Soft Computing

journal homepage: www.elsevier.com/locate/asoc

Free Pattern Search for global optimization

Long Wen, Liang Gao*, Xinyu Li, Liping Zhang

State Key Laboratory of Digital Manufacturing Equipment and Technology, Huazhong University of Science and Technology, Wuhan 430074, China

ARTICLE INFO

Article history:
Received 15 November 2011
Received in revised form 19 March 2013
Accepted 3 May 2013
Available online 28 May 2013

Keywords:
Free Pattern Search
Pattern Search
Free Search
Global optimization

ABSTRACT

An efficient algorithm named Pattern search (PS) has been used widely in various scientific and engineering fields. However, even though the global convergence of PS has been proved, it does not perform well on more complex and higher dimension problems nowadays. In order to improve the efficiency of PS and obtain a more powerful algorithm for global optimization, a new algorithm named Free Pattern Search (FPS) based on PS and Free Search (FS) is proposed in this paper. FPS inherits the global search from FS and the local search from PS. Two operators have been designed for accelerating the convergence speed and keeping the diversity of population. The acceleration operator inspired by FS uses a self-regular management to classify the population into two groups and accelerates all individuals in the first group, while the throw operator is designed to avoid the reduplicative search of population and keep the diversity. In order to verify the performance of FPS, two famous benchmark instances are conducted for the comparisons between FPS with Particle Swarm Optimization (PSO) variants and Differential Evolution (DE) variants. The results show that FPS obtains better solutions and achieves the higher convergence speed than other algorithms.

1. Introduction

Nowadays, the problems become more and more complicated in scientific research, engineering, financial and management field and so on, which creates a demand of more powerful optimizer to solve them within limited time and memory. Over the last decades, nature-inspired algorithms took the responsibility for that and dedicated themselves to the complex problems. Lots of intelligence algorithms had been proposed such as genetic algorithm [1,2] (GA), particle swarm optimization [3] (PSO), differential evolution [4] (DE), human search [5] (HS) and artificial bee colony algorithm [6] (ABC). They show a great potential for global optimization and have been applied to solve various engineering problems [7,8] for their simplification and effectiveness [9].

However, almost all of the algorithms suffer from the prematurity. In order to get a higher quality solution and better performance, hybrid algorithms are used for handling this, such as CPSO [10] (hybrid PSO and Cellular automata), DSSA [11] (hybrid SA and Direct search), DE/BBO [12] (hybrid DE and BBO), DTS (hybrid TS and Direct search) [13]. All of these hybrid algorithms have achieved the good performance. However, the real problems become more and more complex, and the benchmarks which are used to test the performance of algorithms also become more and more complex, at the same time the dimensions of benchmarks increase as well, which makes them more difficult to be solved. Even lots of good algorithms have been designed, this road never ends. This research focuses on this topic and a new algorithm called Free Pattern Search (FPS) has been designed for optimization.

FPS is inspired by Pattern Search (PS) and Free Search (FS), and it extends PS into a population based formation. PS was firstly proposed by Hooke and Jeeves [14] in 1961. Torczon [15] provided a detailed formal definition of PS. As a kind of direct search, PS does not require gradient information at all, so it shares some similarities with modern evolutionary algorithms. The search step size of PS is very crucial for global convergence of PS and it should be reduced only when no increase or decrease in any one parameter further improved the fit [16], even though PS has been proofed to be a global convergence algorithm [15].

Traditional PS did not perform well on the complex and high dimension problems. Hvattum and Glover [17] proposed a new direct search method called SS (Scatter Search) and proved that HJPS (Hooke and Jeeves Pattern Search) was worse than CS (Compass Search) and SS even though the convergence properties of them were similar. Lots of researchers have been dedicated to modify PS for better performances [18–20]. In fact, the empirical convergence is different from theoretical convergence. The former one is the real performance, which has more impacts on the quality of the results.

FS [21,22] is the other resource for FPS. Because of the self-regular management, FS which is a population based algorithm has good global search ability [22]. The acceleration part in FPS uses a FS-inspired part, exactly, a self-regular part to classify the

* Corresponding author. Tel.: +86 27 87559419; fax: +86 27 87543074.
E-mail address: gaoliang@mail.hust.edu.cn (L. Gao).

1568-4946/$ – see front matter © 2013 Elsevier B.V. All rights reserved.
http://dx.doi.org/10.1016/j.asoc.2013.05.004

Nomenclature

PS	Pattern Search
FS	Free Search
PSO	particle swarm optimization
FPS	Free Pattern Search
HJPS	Hooke and Jeeves Pattern Search
DE	differential evolution
DSSA	direct search simulated annealing
DE/BBO	differential evolution with biogeography-based optimization
DTS	directed tabu search
CPSO	cellular particle swarm optimization
ILPSO	integrated learning particle swarm optimizer
LeDE	learning-enhanced differential evolution
CDE	clustering-based differential evolution
M	the pattern matrix
ψ	the current point in Pattern Search
θ	the previous point in Pattern Search
φ	the base point in Pattern Search
Δ	the search step size of pattern
α	the search step sizes factor of the pattern
κ	the reduce factor of pattern
m	the population size of Free Pattern Search
n	the number of the dimension
T	the numbers of steps for local Pattern Search
∂	the rate of the detection range
X_j	the jth individual in the population
x_i	the ith element of an individual

population, and then PS take the responsibility to accelerate them. In order to enhance the exploitation phase and keep the diversity of population, FS works with PS to ensure the exploitation and exploration of FPS as well as other operators.

The rest of the paper is organized as follows. The next section introduces the traditional HJPS. The detailed description of FPS is presented in Section 3. In Section 4, two sets of experiment are applied to evaluate the performance of FPS. Section 5 is the conclusion and future researches.

2. Traditional Pattern Search

The traditional HJPS is a single-point search method, which generates a sequence of non-increasing solutions in whole iterations. The "pattern" which is very important is the neighborhood structure of the base point, and the points on the neighborhood structure are called trials. Fig. 1 shows the HJPS pattern on 2D. The white points are the trials of the black one (base point), as it can be seen clearly that the trials form a grid and the grid is the neighborhood structure of the base point called "pattern".

Typically, the columns of the pattern are the unit vectors in HJPS and it is denoted by the pattern matrix M as showed below:

$$M = \begin{bmatrix} \Delta_1 & -\Delta_1 & 0 & 0 & \cdot & \cdot & 0 & 0 \\ 0 & 0 & \Delta_2 & -\Delta_2 & \cdot & \cdot & 0 & 0 \\ \cdot & \cdot & \cdot & \cdot & \Delta_i & -\Delta_i & \cdot & \cdot \\ 0 & 0 & 0 & 0 & \cdot & \cdot & \Delta_n & -\Delta_n \end{bmatrix}$$

In HJPS, the search step sizes Δ on each dimension are same ($\Delta_i = \Delta_j$). Actually, there are so many types of pattern in the paradigm of PS, such as canonical PS [14] using square with $n \times 2n$ pattern, Rank Ordered PS [23] using $n \times (n+1)$ pattern, Compass

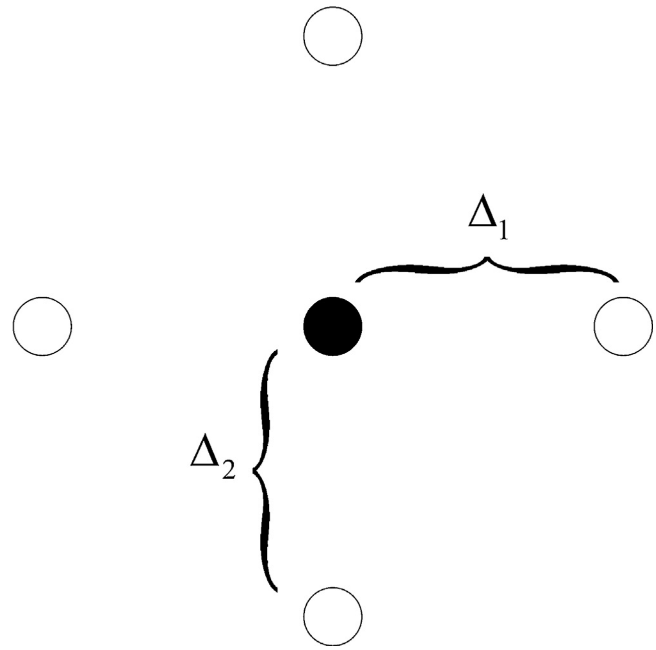

Fig. 1. Illustration of the pattern on 2D.

Search [24] using $n \times 2n$ pattern. The HJPS pattern is a $n \times 2n$ type and it is simple and effective.

There are three kinds of points in HJPS, they are the current point ψ, the base point φ, the previous point θ. The current point is the current solution of the HJPS, the base point is used for detecting better solutions, and then it would be assigned to the current point if it is better. The previous point is the last current point, and it helps the base point to find a profit solution. Initially, the base point is initialized by the current point.

The HJPS contains exploration move (EMove, same with the coordinate search) and pattern move (PMove). The EMove completes the coordinate search on all of the dimensions of the base point to find the best trial near it. The step of EMove is as followed:

Step 1: Construct the pattern M for the base point φ. Initialize the parameter $i = 0$;
Step 2: Testing if $f(\varphi) > f\left(\varphi + M_{:,2i}\right)$ then $\varphi = \varphi + M_{:,2i}$;Otherwise testing if $f(\varphi) > f\left(\varphi + M_{:,2i+1}\right)$ then $\varphi = \varphi + M_{:,2i+1}$.Increment i;
Step 3: If $i > n$, terminated, otherwise go to Step 2.

After the EMove, the PMove would be implemented when the best trial is better than the current point, meaning a better solution has been found. Then the current point ψ and the previous point θ would be upgraded, a new base point φ would be constructed by the current point and the previous point. The formulation of PMove is:

$$\theta = \psi, \psi = \varphi, \varphi = 2\varphi - \theta$$

The flow chart of HJPS is presented in Fig. 2. The search step size of pattern is very important in the PS, and it determines the size of pattern. During the search, it will decrease by κ when no trial is better than the current point.

Such as the minimization $f(x) = x^2$, $x \in (-0.5, 0.5)$, and assume that the initialization current position is the point 0.4 (point A) and the search step sizes is 0.1 shown in Fig. 3. Then the pattern matrix would be [0.1, −0.1] indicating that the trials are the points 0.5 and 0.3. Search the pattern of the base point (EMove) and find that 0.3 is the best trial, so the base point is 0.3 (point a) now. From Fig. 3,