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A novel group search optimizer for multi-objective optimization

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ABSTRACT

In this paper, a novel multi-objective group search optimizer named NMGSO is proposed for solving the multi-objective optimization problems. To simplify the computation, the scanning strategy of the original GSO is replaced by the limited pattern search procedure. To enrich the search behavior of the rangers, a special mutation with a controlling probability is designed to balance the exploration and exploitation at different searching stages and randomness is introduced in determining the coefficients of members to enhance the diversity. To handle multiple objectives, the non-dominated sorting scheme and multiple producers are used in the algorithm. In addition, the kernel density estimator is used to keep diversity. Simulation results based on a set of benchmark functions and comparisons with some methods demonstrate the effectiveness and robustness of the proposed algorithm, especially for the high-dimensional problems.

1. Introduction

Multi-objective optimization has always been one of the hot research topics since many real world optimization problems are multiple criteria in nature. During the past two decades, evolutionary computation (Eiben & Smith, 2003) and swarm intelligence (Eberhart, Shi, & Kennedy, 2001) have gained increasing attention in both academic and engineering fields. So far, many meta-heuristic algorithms have been developed for solving the multi-objective optimization problems (MOPs) (Andrzej, 1985; Coello, 2000). For example, Schaffer (1984) proposed the vector evaluated genetic algorithm (VEGA); Ulungu, Teghem, and Tuyttens (1999) presented a simulated annealing-based approach (MOSA); Deb, Amrit, Agarwal, and Meyarivan (2002) proposed the fast and elitist multi-objective genetic algorithm (NSGA-II); Jaskiewicz (2004) suggested a Pareto memetic algorithm with a scalarizing function-based selection mechanism; Knowles (2006) presented a ParEGO; Köksalan and Phelps (2007) introduced an evolutionary meta-heuristic named EMAPS. As for the multi-objective evolutionary algorithms, population categorization strategy (Goldberg, 1989) based on non-dominance is very important, and based on the concept some algorithms have a fitness assignment scheme (Deb et al., 2002; Fonseca & Fleming, 1993; Horn, Nafploitis, & Goldberg, 1994; Knowles & Corne, 2000; Srinivas & Deb, 1994; Zitzler & Thiele, 1999; Zitzler, Laumanns, & Thiele, 2001). Recently, Zitzler and Künzli (2004) proposed an indicator-based evolutionary algorithm (IBEA); Beume, Naujoks, and Emmerich (2007) presented a hyper volume measure based evolutionary algorithm (SMS-EMOA); Igel, Hansen, and Roth (2007) modified the single objective elitist covariance adaptation strategy (CMA-ES) to handle multiple objectives. In addition, there developed several recent heuristics to generate the efficient frontiers. Nebro et al. (2008) proposed a hybrid approach that used some concepts from evolutionary approaches, whereas Bandyopadhyay, Saha, Maulik, and Deb (2008), Smith, Everson, Fieldsend, Murphy, and Misra (2008) and Zhang, Zhou, and Jin (2008) proposed heuristics without using any evolutionary concepts.

As a new and efficient algorithm based on swarm intelligence, Group Search Optimizer (GSO) (He, Wu, & Saunders, 2006, 2009) adopts the scrounging strategy of house sparrows and employs special animal scanning mechanism to perform searching process. The original GSO was improved by controlling the number of dimensions of allowed variations and by adopting randomness to determine the coefficients of individuals in the next generation (Zhang, Teng, & Li, 2009). The GSO has shown superior performances on high dimensional multi-modal problems (He, 2010; He, Wu, & Saunders, 2009; Li, Xu, Liu, & Wu, 2010; Shen, Zhu, Niu, & Wu, 2009). However, to our knowledge there has no research work about the GSO for multi-objective optimization problems yet, which is the motivation of this research.

In this paper, a novel multi-objective group search optimizer (NMGSO) is proposed for solving the multi-objective optimization problems. We replace the scanning strategy in GSO with the limited pattern search procedure (Ali & Kajee-Bagdadi, 2009) to simplify the computation and improve the performance, design a special mutation with a controlling probability to enrich the search behavior of the rangers to balance the exploration and exploitation at different searching stages, introduce the randomness in

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determining the coefficients of members to enhance the diversity, and use the non-dominated sorting scheme (Deb et al., 2002) and multiple producers to handle multi-objectives. Moreover, we employ the kernel density estimator (Reyes-Sierra & Coello, 2006) to keep diversity. Based on several benchmark functions, we carry out numerical simulations and compare the proposed algorithm with other algorithms based on the widely used metrics (Leung & Wang, 2003), which demonstrates the effectiveness and robustness of the NMGSO.

The remainder of this paper is organized as follows. In Section 2, group search optimizer is briefly introduced. In Section 3, a novel multi-objective GSO is proposed and described in details. Numerical experiments and comparisons are provided in Section 5 based on the benchmark functions described in Section 4. Finally, we end the paper with some conclusions in Section 6.

2. The group search optimizer

Group search optimizer (GSO) (He et al., 2009) is a population-based optimization algorithm, which employs the producer–scrounger (PS) model and the animal scanning mechanism. The population of the GSO is called a group, where each individual is called a member. In the GSO, a group consists of three types of members: producers, scroungers and rangers. Producers perform producing strategy in the way of animal scanning mechanism; scroungers perform scrounging strategy by joining resources uncovered by others; and rangers search for the randomly distributed resources by random walks. In each generation, the best member is treated as the producer, and a number of members except the producer in the group are selected as the scroungers, while the remaining members are regarded as the rangers.

In GSO, each member has a position $X_i^k \in R^n$, a head angle $\phi_i^k = \left(\phi_{i1}^k, \ldots, \phi_{i(n-1)}^k\right) \in R^{n-1}$ and a head direction $D_i^k = (d_{i1}^k, \ldots, d_{in}^k) \in R^n$ that can be calculated from the head angle via a Polar to Cartesian coordinate transformation as follows:

$$\begin{cases} d_{i1}^k = \prod_{p=1}^{n-1} \cos(\phi_{ip}^k) \\ d_{ij}^k = \sin\left(\phi_{i(j-1)}^k\right) \cdot \prod_{p=i}^{n-1} \cos(\phi_{ip}^k) \\ d_{in}^k = \sin\left(\phi_{i(n-1)}^k\right) \end{cases} \tag{1}$$

In GSO, the producer X_p^k scans for the new resource as the white crappie in the scanning field characterized by a maximum pursuit angle $\theta_{\max} \in R^{n-1}$ and a maximum pursuit distance $l_{\max} \in R^1$. The scanning procedure can be described as follows:

(a) The producer randomly samples three points in the scanning field: one point at zero degree, one point in the right hand side hypercube, and one point in the left hand side hypercube, as follows:

$$\begin{cases} X_z = X_p^k + r_1 \cdot l_{\max} \cdot D_p^k(\phi^k) \\ X_r = X_p^k + r_1 \cdot l_{\max} \cdot D_p^k(\phi^k + r_2 \cdot \theta_{\max}/2) \\ X_l = X_p^k + r_1 \cdot l_{\max} \cdot D_p^k(\phi^k - r_2 \cdot \theta_{\max}/2) \end{cases} \tag{2}$$

where $r_1 \in R^1$ is a normally distributed random number with mean 0 and standard deviation 1, and $r_2 \in R^{n-1}$ is a uniformly distributed random number in the range (0,1).

(b) The producer finds the best point among the three points. If the best point is better than its current position, it will fly to this point; otherwise, it will stay in its current position and turn its head to the following new angle:

$$\phi^{k+1} = \phi^k + r_2 \cdot \alpha_{\max} \tag{3}$$

where $\alpha_{\max}$ is the maximum turning angle.

(c) If the producer cannot find a better area after a iterations, it will turn back to zero degree.

$$\phi^{k+a} = \phi^k \tag{4}$$

where a is a pre-defined constant.

The scroungers perform random walk towards the producer as follows:

$$X_i^{k+1} = X_i^k + r_3 \circ (X_p^k - X_i^k) \tag{5}$$

where $r_3 \in R^n$ is a uniformly distributed random sequence in the range (0,1).

In each generation, rangers move to the new point based on a random head angle and a random distance as follows:

$$\begin{cases} X_i^{k+1} = X_i^k + a \cdot r_1 \cdot l_{\max} \cdot D_i^k(\phi_i^k + r_2 \cdot \alpha_{\max}) \\ l_i = a \cdot r_1 \cdot l_{\max} \\ \phi_i^{k+1} = \phi_i^k + r_2 \cdot \alpha_{\max} \end{cases} \tag{6}$$

3. The novel multi-objective group search optimizer

3.1. Multi-objective optimization

Multi-objective optimization can be defined as the problem of finding a vector of decision variables that optimizes a set of objective functions (Andrzej, 1985). Generally speaking, it can be stated as follows: Find the n-dimensional vector $X^* = [x_1^*, x_2^*, \ldots, x_n^*]^T$ that minimizes the m-dimensional vector of objective functions:

$$F(X) = [f_1(X), f_2(X), \ldots, f_m(X)]^T \tag{7}$$

where $X = [x_1, x_2, \ldots, x_n]^T$ is the vector of decision variables.

In multi-objective optimization problems (MOPs), there is often confliction between the different objectives. There may be no such a single solution that is optimal for all the objectives, and the optima may be a set of solutions that are called non-inferior or non-dominated solutions (Coello, 2000) defined as follows:

(a) Pareto dominance: $A \prec B$ if and only if

$$\begin{cases} f_i(A) \leqslant f_i(B), & \forall i \in \{1, 2, \ldots, m\} \\ f_j(A) < f_j(B), & \exists j \in \{1, 2, \ldots, m\} \end{cases} \tag{8}$$

(b) Pareto optimal or Pareto non-dominated: solution A is Pareto optimal (Pareto non-dominated) if and only if

$$!\exists\, X \in R^n : X \prec A \tag{9}$$

The set that contains all the Pareto optimal solutions is called Pareto optimal set, and the area formed by all non-dominated objective vectors is called Pareto front.

3.2. Novel multi-objective group search optimizer

First, when performing the scanning strategy employed by the producer in the original GSO, all the members have to keep the record of the head angle and use a Polar to Cartesian coordinates transformation for updating the position, which is very time consuming. Moreover, the maximum pursuit angle $\theta_{\max}$ is set to be π/a^2 (He et al., 2009). Since the transformation is not linear, the search in different dimension may be not equal. In fact, the searching behavior of producer is a local search around the best solution. The scanning strategy can be transformed into a pattern search in the polar coordinate. In this paper, to simplify the computation and to enhance the local search capability of the producer, the scanning strategy is replaced with a limited pattern search (LPS) (Ali &