GSRA

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Gradient Stochastic Ranking-based multi-indicator Algorithm

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Reference

1. Overview

The proposed algorithm, namely gradient stochastic ranking-based multi-indicator Algorithm (GSRA). The algorithm enhances the convergence of stochastic ranking-based multi-indicator Algorithm (SRA)[1] by developing an efficient environmental selection strategy in the context of many-objective optimization.

2. Background

The framework of SRA is described as follows: First, Generate an initial population of N solutions. At each generation, parent individuals are randomly picked to create offspring. After fitness evaluation, the offspring population is merged with the parent population. Then the indicator values of the merged population are computed. SRA involve two indicators, intuitively they should show different biases, one favors convergence and the other prefers diversity, the random number in the range [0, 1] is used to determine to stochastic ranking in convergence or diversity.

The convergence indicator $I_c(x)$ for comparing solutions are defined as

$$I_c(x) = \sum_{y \in P, y \neq x} -e^{-I_{\epsilon+}(x,y)/0.05}$$

Where, $I_{\epsilon+}$[2] is the minimum distance by which a Pareto set approximation:

$$I_{\epsilon+}(x,y) = \min_{\epsilon}(f_i(x) - \epsilon \leq f_i(y)\,, \mathrm{i} \in \{1, \dots, m\})$$

The diversity indicator $I_d(x)$ for comparing solutions are defined as

$$I_d(x) = \min_{y \in P, y\ precedes\ x} \{I_{SDE}(x,y)\}$$

Where, I_{SDE} [3] is the Shift-based Density Estimation:

$$I_{SDE}(x,y) = \sqrt{\sum_{1 \leq i \leq m} sd(f_i(x), f_i(y))^2}$$

3. Framework of the Proposed Algorithm

Convergence and diversity are two important indicators of evolutionary many-objective optimization problems (MaOPs), In order to highlight the importance of the adaptive capacity for the indicators $I_c(x)$ and $I_d(x)$. The GSRA algorithm employs a gradient stochastic ranking procedure to carry out environmental selection based on multiple indicators and inherits the capability of SRA in maintaining the convergence and diversity. the new method is to control the speed of convergence and divergence values nonlinearly in the course of gradient changes in the two most important indicators. The following definition is derived by applying the above preference relation.

$$\nabla_c^t = \begin{cases} |(I_c^t - I_c^{t-1})/I_c^t| & \mathrm{t} > 1 \\ 1 & \mathrm{t} = 1 \end{cases}$$

$$\nabla_d^t = \begin{cases} |(I_d^t - I_d^{t-1})/I_d^t| & t > 1 \\ 1 & t = 1 \end{cases}$$

Where ∇_c^t is the gradient of convergence, ∇_d^t is the gradient of diversity.

The environmental selection procedure of GSRA is given by Algorithm 1.

Algorithm 1: Gradient Stochastic Ranking Based Environmental Selection

input : combined population $U_t = \{u_1, u_1, \dots, u_{2N}\}$,parameter pc
output: sorted population P_{t+1}

for sweepCounter ← 1 **to** $|U_t|/2$ **do**
  for j←1 **to** $|U_t|$-1 **do**
    Sample $\mathrm{u} \in \mathrm{U}(0,1)$
    if u<p_c **then**
      e←1
    else
      e←0
    end
    if $(\nabla_c^t(u_j) > 1.5)$ and $(\nabla_d^t(u_j) > 1.5)$ and $(\nabla_c^t(u_j) > \nabla_d^t(u_j))$ **then**
      e←1
    end
    if $(e = 0)$ **and** $(I_c(u_j) < I_c(u_{j+1}))$ **then**
      swap(u_j, u_{j+1})
    end
    if $(e = 1)$ **and** $(I_d(u_j) < I_d(u_{j+1}))$ then
      swap(u_j, u_{j+1})
    end
  end
  if *no swap done* **then**
    break;
  end
end
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REFERENCES

[1] Bingdong Li, Ke Tang, Jinlong Li, and Xin Yao, Stochastic Ranking Algorithm for Many-Objective Optimization Based on Multiple Indicators, IEEE Trans. Evol. Comput., vol. 20, no. 6, pp. 924–938, December**.** 2016.

[2] M. Li, S. Yang, and X. Liu, "Shift-based density estimation for Paretobased algorithms in many-objective optimization," IEEE Trans. Evol. Comput., vol. 18, no. 3, pp. 348–365, Jun. 2014.

[3] E. Zitzler and S. Künzli, "Indicator-based selection in multiobjective search," in Parallel Problem Solving From Nature-PPSN VIII.Heidelberg, Germany: Springer, 2004, pp. 832–842.