Lab 7 - Implement and Understand Brain Storm Optimization Algorithm

CSE, SUSTech

Outline of This Lab

- Teaching Assistant
- How Does The BSO Work
- Does The Number of Clusters *k* Matter?
- Test Functions
- Illustrate The Results!

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How Does The BSO Work
-The BSO Algorithm (Main Loop)

1. Initialization: Generate *n* random ideas (individuals) in the search space.
2. Clustering: Group the *n* ideas into *k* clusters using a clustering algorithm (e.g., k-means).
3. Evaluate & Rank: Calculate the fitness of each idea and identify the best idea in each cluster.
4. Apply a disruptive operator to a cluster' best idea with a low probability.
5. Generate New Ideas: For each new idea to be created:
   - ✓ Select one or two clusters.
   - ✓ Create a new idea based on one or two existing ideas in the cluster(s).
   - ✓ Select the next population from old and new ideas.
6. Repeat until a termination criterion is met.

How Does The BSO Work
-Step 1: The Clustering Phase

- Purpose: To group similar solutions, preventing premature convergence and managing diversity.
- Common Method: K-Means Clustering.
  - ✓ The number of clusters, *k*, is a key algorithm parameter.
  - ✓ Each cluster has a center (mean or best of its ideas) and/or a best idea (highest fitness member).
- Why it matters: The cluster structure directly guides the search. Operators treat ideas within a cluster differently than ideas from different clusters.

How Does The BSO Work
-Step 2: The New Idea Generation Operator

This is the core variation operator. To create a new idea X_{new}:

1. Randomly generate a value between 0 and 1;
2. If the value is less than a probability p_one,
   i. Randomly select a cluster;
   ii. Generate a random value between 0 and 1;
   iii. If the value is smaller than a pre-determined probability p_select_best,
      - Select the cluster center and add random values to it to generate new individual.
   iv. Otherwise randomly select an individual from this cluster and add random value to the individual to generate new individual.
3. Otherwise randomly select two clusters to generate new individual
   I. Generate a random value and the two cluster are randomly selected;
   II. If it is less than a pre-determined probability p_select_best, the two clusters' centers are combined and then added with random values to generate new individual;
   III. Otherwise, two individuals from each selected cluster are randomly selected to be combined and added with random values to generate new individual.
4. The newly generated individual is compared with the existing individual with the same individual index, the better one is kept and recorded as the new individual;

How Does The BSO Work
-The "Disruptive" Operator for Innovation

- To prevent getting trapped in local optima, BSO includes a disruptive operator.
- With a very low probability (p_disrupt), a new idea is not created from existing clusters.
- Instead, it is generated randomly in the search space, just like in the initialization step.
- This represents a "wild" or "out-of-the-box" idea that is completely different from the current thinking.
- This mechanism is crucial for maintaining population diversity and global exploration capabilities.

Does The Number of Clusters Matter?

- Implement the BSO algorithm with different number of clusters *k*.

Test Functions
-7 unimodal benchmark functions

- Unimodal functions: f_1-f_5
- f_6 is the step function (one minimum, discontinuous).
- f_7 is a noisy quartic function, where random[0, 1) is a uniformly distributed random variable in [0, 1).

Test function	n	S	f_{min}
$f_1(\mathbf{x}) = \sum_{i=1}^{n} x_i^2$	30	$[-100, 100]^n$	0
$f_2(\mathbf{x}) = \sum_{i=1}^{n} \lvert x_i \rvert + \prod_{i=1}^{n} \lvert x_i \rvert$	30	$[-100, 100]^n$	0
$f_3(\mathbf{x}) = \sum_{i=1}^{n} (\sum_{j=1}^{i} x_j)^2$	30	$[-10, 10]^n$	0
$f_4(\mathbf{x}) = \max_i \{\lvert x_i \rvert, 1 \leq i \leq n\}$	30	$[-100, 100]^n$	0
$f_5(\mathbf{x}) = \sum_{i=1}^{n} [100(x_{i+1} - x_i^2)^2 + (x_i - 1)^2]$	30	$[-100, 100]^n$	0
$f_6(\mathbf{x}) = \sum_{i=1}^{n} (x_i + 0.5)^2$	30	$[-30, 30]^n$	0
$f_7(\mathbf{x}) = \sum_{i=1}^{n} i x_i^4 + random[0, 1)$	30	$[-1.28, 1.28]^n$	0

Test Functions
-8 multimodal benchmark functions

Test function	n	S	f_{min}
$f_8(\mathbf{x}) = \sum_{i=1}^{n} -x_i \sin(\sqrt{\lvert x_i \rvert})$	**30**	$[-500, 500]^n$	**-12569.5**
$f_9(\mathbf{x}) = \sum_{i=1}^{n} [x_i^2 - 10\cos(2\pi x_i) + 10)]$	**30**	$[-5.12, 5.12]^n$	**0**
$f_{10}(\mathbf{x}) = -20\exp\left(-0.2\sqrt{\frac{1}{n}\sum_{i=1}^{n} x_i^2}\right) - \exp\left(\frac{1}{n}\sum_{i=1}^{n}\cos 2\pi x_i\right) +20 + e$	**30**	$[-32, 32]^n$	**0**
$f_{11}(\mathbf{x}) = \frac{1}{4000}\sum_{i=1}^{n} x_i^2 - \prod_{i=1}^{n}\cos\left(\frac{x_i}{\sqrt{i}}\right) + 1$	**30**	$[-600, 600]^n$	**0**
$f_{12}(\mathbf{x}) = \frac{\pi}{n}\left\{10\sin^2(\pi y_1) + \sum_{i=1}^{n-1}(y_i - 1)^2[1 + 10\sin^2(\pi y_{i+1})] +(y_n - 1)^2\right\} + \sum_{i=1}^{n} u(x_i, 10, 100, 4)$, $y_i = 1 + \frac{1}{4}(x_i + 1)$, $u(x_i, a, k, m) = \begin{cases} k(x_i - a)^m, & x_i > a, \\ 0, & -a \leq x_i \leq a, \\ k(-x_i - a)^m, & x_i < -a. \end{cases}$	**30**	$[-50, 50]^n$	**0**
$f_{13}(\mathbf{x}) = 0.1\left\{\sin^2(3\pi x_1) + \sum_{i=1}^{n-1}(x_i - 1)^2[1 + sin^2(3\pi x_{i+1})] +(x_n - 1)^2[1 + \sin^2(2\pi x_n)]\right\} + \sum_{i=1}^{n} u(x_i, 5, 100, 4)$	**30**	$[-50, 50]^n$	**0**
$f_{14}(\mathbf{x}) = \left[\frac{1}{500} + \sum_{j=1}^{25}\frac{1}{j+\sum_{i=1}^{2}(x_i - a_{ij})^6}\right]^{-1}$	**2**	$[-65.536, 65.536]^n$	**1**
$f_{15}(\mathbf{x}) = \sum_{i=1}^{11}\left[a_i - \frac{x_1(b_i^2 + b_i x_2)}{b_i^2 + b_i x_3 + x_4}\right]^2$	**4**	$[-5, 5]^n$	**0.0003075**

Experimental Setup

- 15 Test Minimization Functions (7 unimodal + 8 multimodal benchmark functions).
- Population size 50.
- Maximum function evaluation 500, 000.
- Set the number of clusters *k* to be 2, 4, 6, and 8, respectively
- 30 independent runs for each function and each different *k*.

Illustrate The Results!

Plot 60 (=15x4) figures with one for each test function and each *k*, respectively.

- ✓ x-axis: current generation number.
- ✓ y-axis: average fitness value of the best individual of current population over 30 runs.