Submission Packet for com102s1: NL-SOMA-CLP for Real Parameter Single Objective Bound Constrained Optimization

Files Included in this Packet

Competition Entry:
Submission (com102s1)

- Submission form data
- Paper Upload

Submission Details: com102s1

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Competition

Competition: Competition Real Parameter Single Objective Bound Constrained Optimization

Title

Title: NL-SOMA-CLP for Real Parameter Single Objective Bound Constrained Optimization

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Abstract

Abstract (Maximum 200 words):

This paper presents a competition entry for the Real Parameter Single Objective Bound Constrained Optimization at The Genetic Evolutionary Computation Conference (GECCO) 2022. A new variant of the Self-organizing Migrating Algorithm with CLustering-aided migration and adaptive perturbation vector control (SOMA-CLP) is proposed in this paper, which is titled Non-Linear Population Size Reduction and Nearest Neighbor Leader Selection SOMA-CLP(NL-SOMA-CLP). Overall, NL-SOMA-CLP improves the SOMA-CLP by using two techniques: a) a non-linear automatic reduction of population size and b) the nearest neighbor leader selection strategy.

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Poster Presentation

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NL-SOMA-CLP for Real Parameter Single Objective Bound Constrained Optimization

Anonymous

Abstract

This paper presents a competition entry for the Real Parameter Single Objective Bound Constrained Optimization at The Genetic Evolutionary Computation Conference (GECCO) 2022. A new variant of Self-organizing Migrating Algorithm with CLustering-aided migration and adaptive perturbation vector control (SOMA-CLP) is proposed in this paper, which is titled Non-Linear Population Size Reduction and Nearest Neighbor Leader Selection SOMA-CLP(NL-SOMA-CLP). Overall, NL-SOMA-CLP improves the SOMA-CLP by using two techniques: a) a non-linear automatic reduction of population size and b) a nearest neighbor leader selection strategy.

CCS Concepts: • **Mathematics of computing** → **Evolutionary algorithms**.

Keywords: GECCO 2022 Competition, SOMA, Non-linear population size reduction, Nearest Neighbor Leader Selection

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1 Introduction

Self-Organizing Migrating Algorithm, aka SOMA, is one of the most popular evolutionary algorithm, which draws much attention from academic fields in decades [1, 2]. SOMA generates new solutions based on competitive-cooperative behavior among individuals in a population. The performance of SOMA denpends on a few user-defined parameters, such as the leader selection method and the perturbation in the movement from one particular individual towards another one. Recently, SOMA-based algorithms have begun to appear at GECCO competitions. SOMA-CL select leaders in migration with clustering method[3]. SOMA-CLP improves SOMA-CL by useing a linear adaptation of the prt control parameter[4, 5]. In this paper, a novel algorithm named NL-SOMA-CLP is proposed combines several novel parameter control with SOMA-CLP, such as a nearest neighbor leader selection strategy and Non-Linear Population Size Reduction (NLPSR).

2 NL-SOMA-CLP

The proposed NL-SOMA-NLP can be divided into three steps. The first step performs *All-To-Random* strategy, which uses adaptive perturbation vector. The second step performs *All-To-Cluster-Leaders* strategy, where the leader is selected by nearest neighbor leader selection strategy in clusters which are generated by k-means method. Adaptive perturbation vector control is also included in this step. The third step is non-linear depopulation size reduction, which expands the effective search space under the restriction of limited function evaluations. All three steps define one iteration of the entire algorithm.

2.1 All-To-Random

SOMA is based on the cooperation of individuals. The migration is performed as one particular individual from population towards another individual of the population. Equation 1 presents the process of the migration.

$$x_{i,j}^{g+1} = x_{i,j}^{g} + (x_{Leader,j}^{g} - x_{i,j}^{g}) \cdot t \cdot PRTVector_j \tag{1}$$

This step uses the SOMA with All-To-Random strategy. The leader $x_{Leader,j}^{g}$ is selected randomly from the population for each migrant. Adaptive perturbation vector control method is used to calculate PRT which presents the strength of a perturbation during the migration, as Equation 2.

$$PRT = 0.08 + 0.9(NFE/NFE_{max}) \tag{2}$$

where NFE and NFE_{max} represent the meaning the current number of function evaluations and total number of function evaluations. All-To-Random strategy guarantees the diversity of the individuals in the entire algorithm, which avoids constantly searching near the local optimal solution.

2.2 Clustering of the Mapped Space and All-To-Cluster-Leaders

The k-means clustering method is used to divide all individuals by their parameter values into several clusters. The number of outcome clusters should be 10% of the population size.The leaders $x_{Leader,j}^{g}$ is selected in each of clusters. In

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Table 1. Hyperparameters applied in NL-SOMA-CLP

Param.	NP	$step$	$step_L$	$pathLength$	NP_{min}	NP_{max}
Value	100	0.33	0.11	3.0	10	100

previous works, the leader selection method contains Rank Selection technique, Roulette Selection and Single Cluster Leader[3–5]. We proposed a new leader selection method which called Nearest Neighbor Leader Selection. After the clustering method is finished, each individual is divided into one cluster. The individual with best objective function value of the cluster which contains the specific individual is chose to be the leader of each individual.

The individual $x^g_{i,j}$ is again migrating by discrete steps as Equation 1, where the $x^g_{Leader,j}$ is cluster leader chose by Nearest Neighbor Leader Selection.

2.3 Non-Linear Population Size Reduction

To obtain broader search space at the beginning and better convergence at the end of the overall algorithm, the dynamic population size reduction is introduced[6]. The population size NP is recalculated at the end of each generation, and the worst individuals are removed. The population size follows the non-linear function depending on current number of function evaluations and total number of function evaluations, as Equation 3.

$$NP_{g+1} = round((NP_{min} - NP_{max})NFE_r^{1-NFE_r} + NP_{max}) \quad (3)$$

where $NFE_r = \frac{NFE}{NFE_{max}}$ is the ratio of current number of function evaluations and total number of function evaluations. When the population size decreases in the iterations, the number of outcome clusters in section 2.2 will decrease accordingly.

3 Experimental Settings

We evaluate proposed methods on twelve sophisticated functions with shifted, rotation features. One can find the introductions as well as the solution space distribution on the GECCO competition guidelines [7]. Table. 1 lists the hyperparameters applied in NL-SOMA-CLP. The stopping criterion includes: 1. NL-SOMA-CLP reaches the maximum evaluation numbers (200,000 for 10D problems and 1000,000 for 20D problems); 2. Find the optimal solution of the given problem (the error value is smaller than 1e-8).

4 Experimental Results

Table. 2 and Table. 3 records the absolute value error on 10D and 20D problems, respectively.

Table 2. Experimental results on 10D problems

Func.	**Best**	**Worst**	**Median**	**Mean**	**Std**
1	7.95e-09	1.00e-08	9.19e-09	9.09e-09	5.55e-10
2	2.04e-04	4.59e+00	4.96e-02	1.98e-01	8.15e-01
3	7.07e-09	3.55e-07	9.47e-09	2.07e-08	6.21e-08
4	4.97e+00	2.09e+01	9.95e+00	1.02e+01	3.26e+00
5	8.17e-09	1.00e-08	9.61e-09	9.47e-09	4.52e-10
6	8.81e-02	1.43e+00	6.41e-01	7.50e-01	4.67e-01
7	1.63e-09	9.95e-01	9.48e-09	3.32e-02	1.79e-01
8	9.50e-03	7.38e-01	1.36e-01	3.37e-01	2.99e-01
9	2.29e+02	2.29e+02	2.29e+02	2.29e+02	5.68e-14
10	6.25e-02	3.60e+00	2.50e-01	3.42e-01	6.10e-01
11	8.07e-09	9.94e-09	9.29e-09	9.30e-09	4.94e-10
12	1.61e+02	1.65e+02	1.64e+02	1.64e+02	1.61e+00

Table 3. Experimental results on 20D problems

Func.	**Best**	**Worst**	**Median**	**Mean**	**Std**
1	7.78e-09	9.97e-09	9.63e-09	9.48e-09	5.23e-10
2	1.66e+00	4.91e+01	4.91e+01	3.55e+01	2.07e+01
3	7.25e-09	1.00e-08	9.44e-09	9.29e-09	6.85e-10
4	9.95e+00	5.07e+01	3.33e+01	3.30e+01	9.67e+00
5	9.06e-09	5.44e-01	9.96e-09	6.61e-02	1.28e-01
6	1.19e+01	7.94e+01	4.60e+01	4.47e+01	1.70e+01
7	9.96e-01	2.13e+01	3.00e+00	5.46e+00	6.33e+00
8	1.41e+01	2.20e+01	2.06e+01	2.05e+01	1.29e+00
9	1.81e+02	1.81e+02	1.81e+02	1.81e+02	5.68e-14
10	1.25e-01	1.80e+00	1.92e-01	2.52e-01	2.92e-01
11	8.12e-09	4.13e-02	9.84e-09	1.38e-03	7.42e-03
12	2.32e+02	2.41e+02	2.36e+02	2.37e+02	2.67e+00

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