Submission Packet for com103s1: Opposite Learning and Multi-Migrating Strategy-Based Self-Organizing Migrating Algorithm with the Convergence Monitoring Mechanism

Files Included in this Packet

Competition Entry:
Submission (com103s1)
- Submission form data
- Paper Upload

Submission Details: com103s1

Track: Competition Real Parameter Single Objective Bound Constrained Optimization (4) (**Comp RPSOBCO**)
Overall Submission Status: Received
This Stage Status: Accept (Confirmed)
Form first submitted: 2022-04-09 04:25 CDT
Form last updated: 2022-04-09 04:25 CDT
Note: You are **not** viewing the latest submitted stage of this submission.
Latest stage: com103s3 (the "Conference Presentation" stage) details

Competition

Competition: Competition Real Parameter Single Objective Bound Constrained Optimization

Title

Title:
Opposite Learning and Multi-Migrating Strategy-Based Self-Organizing Migrating Algorithm with the Convergence Monitoring Mechanism

Author Information

Author 1:
Name: Yongfeng Gu
Email: guyongfeng.gy@antgroup.com
Company/Institution: Ant Group
2nd Company/Institution:
Country: China
Would this person present the submission at the conference? (NOTE: If the submission is accepted, at least one author must register by the early registration and present the paper at the conference. Any other authors who attend must also register, but as regular attendees.): Yes
Is this person in the organizing or program committee? No

Author 2:
Name: Hao Ding
Email: luoyan.dh@antgroup.com
Company/Institution: Ant Group
2nd Company/Institution:
Country: China
Would this person present the submission at the conference? (NOTE: If the submission is accepted, at least one author must register by the early registration and present the paper at the conference. Any other authors who attend must also register, but as regular attendees.): No
Is this person in the organizing or program committee? No

Author 3:
Name: Hua Wu
Email: wuhua.wh@antgroup.com
Company/Institution: Ant Group
2nd Company/Institution:
Country: China
Would this person present the submission at the conference? (NOTE: If the submission is accepted, at least one author must register by the early registration and present the paper at the conference. Any other authors who attend must also register, but as regular attendees.): No
Is this person in the organizing or program committee? No

Author 4:
Name: Jun Zhou
Email: jun.zhoujun@antgroup.com
Company/Institution: Ant Group
2nd Company/Institution:
Country: China
Would this person present the submission at the conference? (NOTE: If the submission is accepted, at least one author must register by the early registration and present the paper at the conference. Any other authors who attend must also register, but as regular attendees.): No
Is this person in the organizing or program committee? No

Abstract

Abstract (Maximum 200 words):

This paper introduces a novel competition entry on Real Parameter Single Objective Bound Constrained Optimization at GECCO 2022 conference, namely Opposite learning and Multi-migrating strategy-based Self-Organizing Migrating Algorithm with Convergence monitoring mechanism (OMC_SOMA). Specifically, OMC_SOMA induces three techniques to improve the naive SOMA in the aspects of population initialization, convergence monitoring, and migrating strategies. Preliminary experiments on the 12 test functions reveal a good performance of our proposed method.

Paper Upload

Paper Upload:

Type: pdf
Size: 378KB
Pages: 2
Uploaded: Apr 09
MD5: c80f927d3652c6ab7578ac67b5bb0cf8
Original Name: 2022_GECCO_OMCSOMA_final.pdf

Poster Presentation

Please indicate whether you will be presenting a poster: Yes

Edited for Publication

This is not the program stage. The program stage, Stage 2: Camera-Ready Material, **has not** been approved. view

Opposite Learning and Multi-Migrating Strategy-Based Self-Organizing Migrating Algorithm with the Convergence Monitoring Mechanism

A competition entry on Real Parameter Single Objective Bound Constrained Optimization at GECCO 2022 conference

Anonymous

Abstract

This paper introduces a novel competition entry on Real Parameter Single Objective Bound Constrained Optimization at GECCO 2022 conference, namely Opposite learning and Multi-migrating strategy-based Self-Organizing Migrating Algorithm with Convergence monitoring mechanism (OMC_SOMA). Specifically, OMC_SOMA induces three techniques to improve the naive SOMA in the aspects of population initialization, convergence monitoring, and migrating strategies. Preliminary experiments on the 12 test functions reveal a good performance of our proposed method.

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

Keywords: SOMA, Opposite-learning, Multi-migrating strategy, Convergence monitoring, GECCO 2022 Competition

ACM Reference Format:

Anonymous. 2022. Opposite Learning and Multi-Migrating Strategy-Based Self-Organizing Migrating Algorithm with the Convergence Monitoring Mechanism: A competition entry on Real Parameter Single Objective Bound Constrained Optimization at GECCO 2022 conference. In *GECCO '22 Companion: Genetic and Evolutionary Computation Conference, July 09–13, 2022, Boston, US.* ACM, New York, NY, USA, 2 pages. https://doi.org/XXXXXXX.XXXXXXX

1 Introduction

Self-Organizing Migrating Algorithm (SOMA [1]) is a modern swarm-intelligence evolutionary algorithm, which has derived a large body of variants [2, 3] in recent years. The core insight of SOMA is the migration process where all individuals move toward the best individual, which is similar to the other evolutionary algorithms, e.g., Particle Swarm Optimization (PSO) and Ant Colony Optimization (ACO) algorithms. Due to its unique migrating strategy, SOMA can quickly approach the optimum and frequently appear in the fields of evolutionary-related conferences and competitions [4, 5]. This paper presents the competition entry OMC_SOMA, a novel variant of SOMA, which utilizes the opposite learning-based initialization, multi-migrating strategy, and convergence monitoring mechanism.

2 OMC_SOMA

This section introduces the three techniques used in the OMC_SOMA method. Considering the drawbacks of the naive SOMA method, we make the following improvements: Firstly, we employ opposite learning to initialize the population to enlarge the search space. Secondly, we induce a multi-migrating strategy to increase population diversity. Finally, we keep the convergence monitoring mechanism to avoid the SOMA falling trapped into a local optimum.

2.1 Opposite Learning-based Initialization

Population initialization takes a key role in evolutionary algorithms, which greatly affects the convergence speed and quality of solutions. Popular methods include the pseudo-random initialization, chaotic initialization, and opposite learning-based initialization [6, 7]. We can hardly find a universal method for all situations but we can try to search for a suitable one under a specific testbed.

In OMC_SOMA, we employ the opposite learning-based initialization due to its good searching efficiency for potential large space and good performance in the experiments We first randomly initialize an original population $\{x_i\}_{i=1}^{NP}$ and then construct the opposite population $\{\hat{x}_i\}_{i=1}^{NP}$ by equation 1. $NP \in R$ is the population size. Then, we select the Top-NP individuals as the initialized population of OMC_SOMA.

$$\hat{x}_{i,j} = (UB_j + LB_j) - x_{i,j} \tag{1}$$

where the $x_{i,j}$ and $\hat{x}_{i,j}$ denote the value of the j-th dimension of the i-th individual in the original and opposite population, respectively. UB_j and LB_j denote the upper bound and lower bound of the j-th dimension, respectively.

GECCO '22 Companion, July 09–13, 2022, Boston, US

ACM ISBN 978-1-4503-XXXX-X/22/06.
https://doi.org/XXXXXXX.XXXXXXX

2.2 Multi-Migrating Strategy

The migrating strategy is another key point in SOMA, which determines the way the population moves toward an optimum. the popular strategies includes the *AllToOne*, *AllToRand*, and *AllToCLP*. AllToOne [1] strategy considers the individual with the best fitness value as the leader for the whole population. AllToRand [1] strategy selects a random leader for each individual. AllToCLP [5] strategy clusters evaluated individuals and then move them to their corresponding cluster leader. Equation 2 shows the movement pattern of individual x_i during the migration process.

$$x_i = x_i + (x_L - x_i) \cdot t \cdot PRTVector \tag{2}$$

where x_L denotes the selected leader for x_i. $t \in R$ controls the move distance. $PRTVector \in \{0,1\}^D$ guides the direction vector. D is the problem dimension.

In OMC_SOMA, we induce the multi-migrating strategy by means of selection probabilities p_o, p_r, p_c, each of which determines the possibility to choose the corresponding migrating strategy. We expect this combinatorial strategy can make SOMA more robust and be capable of dealing with diverse optimization problems.

2.3 Convergence Monitor Mechanism

To avoid SOMA getting trapped into the local optimum for a long time, we employ the convergence monitor mechanism for SOMA. Specifically, we record the best fitness value we find so far, i.e., fit_{bsf}, and count the times of migrations that fit_{bsf} does not change. The longer the fit_{bsf} does not change, the more possibility SOMA gets trapped into a local optimum. Then we choose the opposite learning to construct the opposite population instead of the current population since we expect to jump to another space of the feasible region to find the real optimum.

We set the convergence threshold $countMax$ to 20, that is, when we monitor that fit_{bsf} does not change for consecutive 20 migrations, we believe that SOMA possibly gets trapped into a local optimum, and re-initializes the whole population by the opposite learning technique.

3 Experiments

The testbed includes the 12 functions with different features (shift, rotation, multi-peak, and hybrid) given by the GECCO problems statement report [8]. The hyper-parameters in OMC_SOMA are the following: population size NP=100, $step$=0.33, $pathLength$=3.0, prt=0.5, p_o=0.4, p_r=0.2, p_c=0.4, $coutMax$=20. For other control parameters like the stopping criterion, please refer to the problems statement report [8].

Table 1 and Table 2 list the experimental results on 10 D and 20 D problems, respectively. Due to the space limitation, the detailed results are uploaded to the website [1].

[1] https://github.com/AnonymousUser0407/GECCO2022CMP

Table 1. Results for 10 D

Func.	Best	Worst	Median	Mean	Std
1	6.41e-09	9.97e-09	9.80e-09	9.39e-09	8.68e-10
2	2.18e-06	6.96e-02	1.68e-03	7.22e-03	1.31e-02
3	6.07e-09	1.42e-06	9.30e-09	1.03e-07	3.52e-07
4	2.98e+00	1.39e+01	6.96e+00	7.20e+00	3.04e+00
5	6.33e-09	9.99e-09	9.50e-09	8.93e-09	1.08e-09
6	3.57e-02	2.37e+00	3.86e-01	7.44e-01	6.36e-01
7	5.15e-09	9.95e-01	1.39e-08	1.33e-01	3.38e-01
8	8.24e-03	7.87e-01	4.31e-01	3.97e-01	2.98e-01
9	1.33e-02	2.29e+02	2.29e+02	2.22e+02	4.12e+01
10	8.61e-09	3.79e+00	2.50e-01	7.90e-01	1.27e+00
11	7.56e-09	2.25e-08	9.62e-09	9.79e-09	2.45e-09
12	1.59e+02	1.65e+02	1.64e+02	1.64e+02	1.30e+00

Table 2. Results for 20 D

Func.	Best	Worst	Median	Mean	Std
1	7.08e-09	9.99e-09	9.70e-09	9.46e-09	6.32e-10
2	1.84e+00	4.91e+01	4.91e+01	4.13e+01	1.64e+01
3	8.30e-09	1.00e-08	9.59e-09	9.46e-09	4.95e-10
4	1.39e+01	3.88e+01	2.24e+01	2.30e+01	6.37e+00
5	9.61e-09	1.79e-01	9.86e-09	1.49e-02	4.06e-02
6	1.55e+01	2.95e+03	8.30e+01	3.26e+02	6.30e+02
7	3.44e-05	3.29e+01	3.26e+00	8.84e+00	9.95e+00
8	2.04e+01	2.35e+01	2.13e+01	2.13e+01	6.98e-01
9	1.01e+02	1.81e+02	1.81e+02	1.78e+02	1.42e+01
10	6.25e-02	3.51e+00	1.89e-01	3.50e-01	6.59e-01
11	9.03e-09	4.47e-04	1.58e-08	1.79e-05	8.03e-05
12	2.31e+02	2.57e+02	2.35e+02	2.38e+02	7.11e+00

References

[1] Quoc Bao Diep, Ivan Zelinka, and Swagatam Das. Self-organizing migrating algorithm pareto. *MENDEL*, 25(1):111–120, 2019.

[2] Quoc Bao Diep. Self-organizing migrating algorithm team to team adaptive - SOMA T3A. In *CEC '19: Congress on Evolutionary Computation*, pages 1182–1187. IEEE, 2019.

[3] Pavel Krömer, Jan Janousek, and Jan Platos. Random key self-organizing migrating algorithm for permutation problems. In *CEC '19: Congress on Evolutionary Computation*, pages 2878–2885. IEEE, 2019.

[4] Tomas Kadavy, Michal Pluhacek, Adam Viktorin, and Roman Senkerik. Self-organizing migrating algorithm with clustering-aided migration. In *GECCO '20: Genetic and Evolutionary Computation Conference, Companion Volume*, pages 1441–1447. ACM, 2020.

[5] Tomas Kadavy, Adam Viktorin, Michal Pluhacek, and Stanislav Kovar. On modifications towards improvement of the exploitation phase for SOMA algorithm with clustering-aided migration and adaptive perturbation vector control. In *SSCI '21: Symposium Series on Computational Intelligence*, pages 1–8. IEEE, 2021.

[6] Borhan Kazimipour, Xiaodong Li, and A. Kai Qin. A review of population initialization techniques for evolutionary algorithms. In *CEC '14: Congress on Evolutionary Computation*, pages 2585–2592. IEEE, 2014.

[7] Borhan Kazimipour, Mohammad Nabi Omidvar, Xiaodong Li, and A. Kai Qin. A novel hybridization of opposition-based learning and cooperative co-evolutionary for large-scale optimization. In *CEC '14: Congress on Evolutionary Computation*, pages 2833–2840. IEEE, 2014.

[8] Abhishek Kumar, Kenneth V. Price, Ali Wagdy Mohamed, Anas A. Hadi, and P. N. Suganthan. Problem definitions and evaluation criteria for the 2022 special session and competition on single objective bound constrained numerical optimization. In *Technical Report, Nanyang Technological University*, pages 1–20, 2021.