Submission Packet for com104s1: Zeroth-Order Covariance Matrix Adaptation Evolution Strategy for Single Objective Bound Constrained Numerical Optimization Competition

Files Included in this Packet

Competition Entry:
Submission (com104s1)

- Submission form data
- Paper Upload

Submission Details: com104s1

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 23:58 CDT
Form last updated: 2022-04-09 23:58 CDT
Note: You are **not** viewing the latest submitted stage of this submission.
Latest stage: com104s3 (the "Conference Presentation" stage) details

Competition

Competition: Competition Real Parameter Single Objective Bound Constrained Optimization

Title

Title:
Zeroth-Order Covariance Matrix Adaptation Evolution Strategy for Single Objective Bound Constrained Numerical Optimization Competition

Author Information

Author 1:
Name: Yue Ning
Email: ningyue.ning@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: Daohong Jian
Email: daohong.jdh@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):

The paper represents a competition entry for the competition on bound constrained single objective numerical optimization at The Genetic and Evolutionary Computation Conference (GECCO) 2022 by a hybrid algorithm named Zeroth-Order Covariance Matrix Adaptation Evolution Strategy (ZO-CMAES).

Paper Upload

Paper Upload:

Type: pdf
Size: 385KB
Pages: 2
Uploaded: Apr 09
MD5: de71dd47f5cf49c894a12bbfb5db0eb4
Original Name: 2022_GECCO_ZOCMAES_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

Zeroth-Order Covariance Matrix Adaptation Evolution Strategy for Single Objective Bound Constrained Numerical Optimization Competition

Anonymous

Abstract

The paper represents a competition entry for the competition on bound constrained single objective numerical optimization at The Genetic and Evolutionary Computation Conference (GECCO) 2022[3] by a hybrid algorithm named Zeroth-Order Covariance Matrix Adaptation Evolution Strategy (ZO-CMAES).

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

Keywords: CMAES, Zeroth-Order, CEC 2022

ACM Reference Format:
Anonymous. 2022. Zeroth-Order Covariance Matrix Adaptation Evolution Strategy for Single Objective Bound Constrained Numerical Optimization Competition. 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

Zeroth-Order Covariance Matrix Adaptation Evolution Strategy (ZO-CMAES) is a hybrid algorithm, which combines the advantages of Covariance Matrix Adaptation Evolution Strategy (CMAES[1]) and Zeroth-Order Optimization (ZO[4]). CMAES is considered an efficient evolutionary algorithm and used to search global optima of unconstrained optimization problems. The Zero-Order optimization (ZO) mentioned in this article is a general term for a class of algorithms designed using the idea of difference technology. ZO can be used to quickly search for local optima. ZO-CMAES combines the global search capabilities of CMAES with the fast local search capabilities of ZO, it improves the stability of the final result of the optimization process.

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

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

2 ZO-CMAES

The ZO-CMAES represents a hybrid algorithm that improves the stability of the original CMAES. ZO is used to generate new candidate local solutions after each iteration of CMAES. At the same time, the partial of local solutions can be used as extended information to calculate mean value and covariance matrix for next iteration of CMAES.

2.1 Global Search with CMAES

The capability of global search comes from the original CMAES proposed by Hansen[1]. The improvement of ZO-CMAES is the novel calculation logic of the mean value. Equation 1 shows the calculation the mean value in each generation.

$$m \leftarrow m + c_m \sum_{i=1}^{\mu} w_i (x_{i:\lambda} - m_{old}) \tag{1}$$

where m denotes the mean value in the current generation. c_m denotes a hyper-parameter that measures the importance of the previous generation mean value and the current generation mean value. w_i denotes the importance of each individual. λ denotes the number of individuals in the population. $x_{i:\lambda}$ denotes sampled value of i-th individual. μ denotes top-μ individuals. m_{old} is the mean value of the last generation.

The original update method of mean value m in CMAES is : $m \leftarrow m + c_m \sum_{i=1}^{\mu} w_i x_{i:\lambda}$. As we can see, ZO-CMAES utilizes the mean value from the last iteration, which allows the algorithm to obtain more global information. An interesting idea is that the mean value can also be computed by natural gradients [2, 5], which can be computed by difference technology. This is the second intuitive idea to deeply combine ZO and CMAES.

2.2 Local Search with ZO

ZO requires only a small number of iterations to obtain local optimal solutions. Therefore, it can be applied to calculate the search path at the local search stage. The intermediate results of the local search process can be recorded and passed to the CMAES. These intermediate results can provide more local information for CMAES and speed up the convergence speed of CMAES. The main formula of ZO is as follows:

$$\hat{\nabla}_x f(x) = \mathbb{E}_{u\ p(u)} [\frac{f(x + \epsilon u) - f(x)}{\epsilon} u] \tag{2}$$

where ϵ is the radius of perturbation. $p(\mu)$ is the pre-defined distribution of μ. $f(x+\epsilon\mu)$ represents the evaluation value of some points within a determined region of the sampled solution to find gradient information through perturbations and predefined distributions. $f(x)$ denotes the evaluation value of sampled solution (individual).

Equation 2 describes how to calculate the zero-order gradient. ZO uses zero-order gradient instead of traditional one-order or two-order gradient to find the local optima. Specifically, CMAES generates feasible results during the search process, and these feasible results serve as the initial point of ZO, which can effectively utilize the local search ability of ZO.

2.3 Selection of candidate solutions

There are two ways to combine solutions generated by ZO and CMAES, called as ZO-after-CMAES and ZO-in-CMAES.

ZO-after-CMAES means that ZO uses only the solution generated by each CMAES iteration as its initial point. Better solutions can be found earlier in the CMAES iteration. It is a very simple hybrid algorithm idea.

Different from ZO-after-CMAES, in ZO-in-CMAES, solutions generated by ZO affect the next iteration of CMAES by combinational population. The final candidate solutions are selected from the local solutions generated by ZO and the sampled solutions based on the normal distribution generated from the covariance matrix in CMAES. First, ZO-CMAES combines all candidate solutions. Second, it randomly selects a population-sized subset of solutions from the combined candidate solutions as the next generation population. Equation 3 shows the detailed selection process of ZO-in-CMAES.

$$C_{new} = random\_select(C_{zo} \cup C_{cmaes}, popsize) \qquad (3)$$

where C_{zo} denotes the set of the local solutions from ZO and C_{cmaes} denotes the set of global solutions from CMAES. $popsize$ is size of the population. Function $random\_select(S, a)$ will randomly select a samples from set S ($a \leq |S|$).

The implementation of candidate solutions will improve the quality of the local population. By adding small disturbances, the algorithm can converge faster without destroying its global search ability.

3 Experiments

This section presents the experimental settings and results of ZO-CMAES. The hyper-parameters affect the results and robustness of the algorithm, especially the global search ability of CMAES is greatly affected by the hyperparameter sigma. The size of the population also has a big impact on the algorithm, both in terms of speed and results.

The values of the control parameters for ZO-CMAES were following: sigma=50, size of size of population ($popsize\_factor \times popsize = 10 \times 11$), number of iterations of ZO (num_zo)=10,

Table 1. Experimental results on 10 D problems

FID	Best	Worst	Median	Mean	Std
1	9.50e-11	7.25e-06	9.06e-08	7.86e-07	1.49e-06
2	3.21e-10	8.92e+00	1.99e+00	3.31e+00	3.74e+00
3	1.16e-08	4.74e+01	2.55e-08	2.32e+00	8.73e+00
4	1.47e-09	4.97e+00	1.99e+00	2.12e+00	1.38e+00
5	7.76e-11	6.61e-10	3.14e-10	3.31e-10	1.52e-10
6	1.30e-01	7.83e+02	1.78e+00	3.00e+01	1.40e+02
7	9.43e-09	2.50e+01	1.80e+00	9.39e+00	1.00e+01
8	3.50e-01	2.15e+01	2.07e+01	1.61e+01	8.45e+00
9	2.29e+02	2.29e+02	2.29e+02	2.29e+02	1.19e-04
10	1.00e+02	2.55e+02	1.01e+02	1.28e+02	5.53e+01
11	1.50e-08	3.00e+02	2.27e-08	1.00e+01	5.39e+01
12	1.63e+02	1.65e+02	1.63e+02	1.64e+02	5.51e-01

The seed is set as a list from 1 to 30 to generate random properties for evaluation of the stability of the algorithm.

4 Results

Due to the space limitation, we only list the best value, worst value, median value, mean value and standard deviation of 12 functions on 10 D problems at this version of paper. (see Table. 1). The detailed experimental results will be updated on a online supplementary material in the future.

From these results, we can see that ZO-CMAES can reach the near-optimal solutions (error value smaller than 1e-8) in function 1, 2, 4, and 7 and obtain a relatively good standard deviation in the mean time. In a nutshell, ZO-CMAES combine the global search (from CMAES) and local search (from ZO), which makes it possible to achieve a good performance on the given 12 test functions.

References

[1] Nikolaus Hansen. 2016. The CMA Evolution Strategy: A Tutorial. *CoRR* abs/1604.00772 (2016). arXiv:1604.00772 http://arxiv.org/abs/1604.00772

[2] Kakade and Sham M. 2001. A Natural Policy Gradient. In *Advances in Neural Information Processing Systems*, T. Dietterich, S. Becker, and Z. Ghahramani (Eds.), Vol. 14. MIT Press. https://proceedings.neurips.cc/paper/2001/file/4b86abe48d358ecf194c56c69108433e-Paper.pdf

[3] Abhishek Kumar, Kenneth V. Price, Ali Wagdy Mohamed, Anas A. Hadi, and P. N. Suganthan. 2022. Problem Definitions and Evaluation Criteria for the CEC 2022 Special Session and Competition on Single Objective Bound Constrained Numerical Optimization. https://github.com/P-N-Suganthan/2022-SO-BO/blob/main/CEC2022%20TR.pdf

[4] Sijia Liu, Pin-Yu Chen, Bhavya Kailkhura, Gaoyuan Zhang, Alfred O. Hero III, and Pramod K. Varshney. 2020. A Primer on Zeroth-Order Optimization in Signal Processing and Machine Learning. *CoRR* abs/2006.06224 (2020). arXiv:2006.06224 https://arxiv.org/abs/2006.06224

[5] Akimoto Youhei, Auger Anne, and Hansen Nikolaus. 2014. Comparison-Based Natural Gradient Optimization in High Dimension. In *Genetic and Evolutionary Computation Conference GECCO'14*. ACM, Vancouver, Canada. https://hal.inria.fr/hal-00997835