Foundations and Recent Advances on Natural Evolution Strategies

Masahiro Nomura (nomura.m.ad@m.titech.ac.jp), Isao Ono (isao@c.titech.ac.jp)

Abstract:

Natural evolution strategies (NES) is a promising family for black-box function optimization. Instead of finding the optimal solution itself, NES aims to find the parameter of a probability distribution that minimizes the expected evaluation value of the solution sampled from the probability distribution. NES updates the parameter of the distribution using an estimated natural gradient. The goal of this tutorial is to summarize Foundations and Recent Advances of NES, with discussions of the relationship between NES and covariance matrix adaptation evolution strategy (CMAES). We also introduce how we can implement and apply NES/CMA-ES easily for both research and practical purposes. We will conclude the tutorial with future directions.

Outline of Tutorial Structure:

This tutorial consists of the following contents (total 2 hours).

(1) Introduction to NES (Isao Ono; 30 min): We will introduce general idea of NES [15] and provide intuition why NES is a promising framework by describing concrete optimization procedure. We also introduce a simple and promising variant of NES, exponential natural evolution strategy (xNES) [5], to highlight its search principle.

(2) Theoretical Foundations (Masahiro Nomura; 30 min): This section will introduce the theoretical foundations [3–5,13,14] to complement why NES is important, which is described in the first section via an intuitive way. We also cover the relation [2] of NES to covariance matrix adaptation evolution strategy (CMA-ES) [6, 7].

(3) Recent Advances (Masahiro Nomura; 30 min): This section will cover recent NES methods to handle emerging practical challenges such as implicit constraint [11], slow expansion of probability distribution [8], high-dimensional problems [9], and learning rate adaptation [10]. In particular, the recent methods such as DX-NES-IC [11] and 1 CR-FM-NES [9] significantly improves the conventional evolution strategies including CMA-ES [6] and Sep-CMA [12].

(4) Implementations (Masahiro Nomura; 20 min): This section will introduce cmaes1, an open-source Python package for NES/CMA-ES, and demonstrate how it helps us use NES/CMA-ES easily for both research and practical purposes.

(5) Conclusion and QAs (Both Presenters; 10 min): This section will conclude the tutorial by summarizing the previous sections and presenting remaining research challenges of the area. There will also be a live QA session. We hope that participants will be able to:

- understand fundamental concepts and methods of NES
- be familiar with recent advances to address practical challenges such as implicit constraint and high-dimensional problems
- know how to implement or apply NES/CMA-ES to real-world problems

- be aware of remaining challenges and opportunities in the relevant field

We will publish all materials including slides and demo code after the tutorial on our tutorial website.

Intended audience

We do not assume any knowledge of NES for the participants, and then the level of the tutorial is introductory. However, participants are expected to have basic knowledge of probability theory and statistics.

Organizer/Presenter

Masahiro Nomura (nomura.m.ad@m.titech.ac.jp). is working for CyberAgent as research scientist, and is a Ph.D. student in the Department of Computer Science at Tokyo Institute of Technology, advised by Prof. Isao Ono. His current research focuses on NES and its extension with learning rate adaptation. Some of his recent work has been published at prominent conferences, including AAAI, CEC, CIKM, EvoStar, GECCO, and IJCAI.

Isao Ono (isao@c.titech.ac.jp). is an associate professor of Department of Computer Science at Tokyo Institute of Technology. His research interests include real-coded genetic algorithms, natural evolution strategies, genetic algorithms for combinatorial optimization such as traveling salesman problems, and their applications.

References

[1] Youhei Akimoto and Nikolaus Hansen, Cma-es and advanced adaptation mechanisms, Proceedings of the genetic and evolutionary computation conference companion, 2022, pp. 1243–1268.

[2] Youhei Akimoto, Yuichi Nagata, Isao Ono, and Shigenobu Kobayashi, Bidirectional relation between cma evolution strategies and natural evolution strategies, International conference on parallel problem solving from nature, 2010, pp. 154–163.

[3] Shun-Ichi Amari, Natural gradient works efficiently in learning, Neural computation 10 (1998), no. 2, 251–276.

[4] Shun-Ichi Amari and Scott C Douglas, Why natural gradient?, Proceedings of the 1998 ieee international conference on acoustics, speech and signal processing, icassp'98 (cat. no. 98ch36181), 1998, pp. 1213–1216.

[5] Tobias Glasmachers, Tom Schaul, Sun Yi, Daan Wierstra, and J¨urgen Schmidhuber, Exponential natural evolution strategies, Proceedings of the 12th annual conference on genetic and evolutionary computation, 2010, pp. 393–400.

[6] Nikolaus Hansen, The CMA Evolution Strategy: A Tutorial, arXiv preprint arXiv:1604.00772 (2016).

[7] Nikolaus Hansen, Sibylle D M¨uller, and Petros Koumoutsakos, Reducing the Time Complexity of the Derandomized Evolution Strategy with Covariance Matrix Adaptation (CMA-ES), Evolutionary computation 11 (2003), no. 1, 1–18.

[8] Masahiro Nomura and Isao Ono, Natural evolution strategy for unconstrained and implicitly constrained problems with ridge structure, 2021 ieee symposium series on computational intelligence (ssci), 2021, pp. 1–7.

[9] , Fast moving natural evolution strategy for high-dimensional problems, 2022 ieee congress on evolutionary computation (cec), 2022, pp. 1–8.

[10] , Towards a principled learning rate adaptation for natural evolution strategies, International conference on the applications of evolutionary computation (part of evostar), 2022, pp. 721–737.

[11] Masahiro Nomura, Nobuyuki Sakai, Nobusumi Fukushima, and Isao Ono, Distanceweighted exponential natural evolution strategy for implicitly constrained black-box function optimization, 2021 ieee congress on evolutionary computation (cec), 2021, pp. 1099– 1106.