An Adaptive Population-based Simplex Method for Continuous Optimization

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ABSTRACT

This paper proposes a new population-based simplex method for continuous function optimization. The proposed method, called Adaptive Population-based Simplex (APS), is inspired by the Low-Dimensional Simplex Evolution (LDSE) method. LDSE is a recent optimization method, which uses the reflection and contraction steps of the Nelder-Mead Simplex method. Like LDSE, APS uses a population from which different simplexes are selected. In addition, a local search is performed using a hyper-sphere generated around the best individual in a simplex. APS is a tuning-free approach, it is easy to code and easy to understand. APS is compared with five state-of-the-art approaches on 23 functions where five of them are quasi-real-world problems. The experimental results show that APS generally performs better than the other methods on the test functions. In addition, a scalability study has been conducted and the results show that APS can work well with relatively high-dimensional problems.

KEYWORDS

Continuous Function Optimization, Low-dimensional Simplex Evolution, Nelder-Mead Simplex, Population-based Optimization Methods, Triangle Evolution

1. INTRODUCTION

Many optimization algorithms have been proposed for solving the continuous nonlinear function optimization problem:

\[
\min f(X) : X_{\text{min}} \leq X \leq X_{\text{max}}
\]

The vector \( X = (x_1,...,x_D) \) is composed of \( D \) real-valued variables, and the vectors \( X_{\text{min}} \) and \( X_{\text{max}} \) are assumed finite and to satisfy \( X_{\text{min}} < X_{\text{max}} \). The function \( f(X) \) is typically multimodal, so that local optima do not in general correspond to global optima. Examples for some well-known optimization methods used to solve this problem are Genetic Algorithms (GA) (Goldberg 1989), Particle Swarm Optimization (PSO) (Kennedy and Eberhart 1995) and Differential Evolution (DE) (Storn and Price 1995).

In this paper we are looking for a method that is easy to understand, easy to code, easy to use, but nevertheless efficient:

- Easy to use--requires no tuning and has few parameters (ideally, none that are visible to the user).

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Bio-inspired algorithms (Olariu and Zomaya 2005) may be good candidates, but they are coming from the 3D world and most of them only are good in low dimensional problems.

Hence the idea was to “revisit” the classical Nelder-Mead (NM) simplex method (Nelder and Mead 1965), which is both purely geometrical and nevertheless quite intuitive and easy to implement. However, NM is well known to be bad for multimodal problems because it is easily trapped into a local optimum (Lagarias et al. 1998). In addition, NM suffers when applied to large dimensional problems (Wright 1996). Consequently, several modifications to NM have been proposed in the literature to improve its performance for global optimization (e.g. Zhao et al. 2009 and Gao and Han 2012). A recent modification has been proposed by Karimi and Siarry (2012) where a global optimization method based on the NM method was proposed. The proposed method, called Global Simplex Optimization (GSO), incorporates a multi-stage, stochastic and weighted version of the NM reflection operator. GSO generally performed better than five optimization methods (including CMA-ES (Hansen 2006)) on 17 functions. However, no single problem in their study has a dimension greater than 10.

One interesting approach has been proposed by Luo and Yu (2012) where DE and NM are combined together. The proposed approach, called Low-dimensional Simplex Evolution (LDSE), is a population-based approach that uses the reflection and contraction operators of NM with an extra step where an individual with fitness worse than the average fitness of the population takes a step either toward the best individual in the population (to improve its fitness) or away from the worse individual (to increase diversity). The method uses a low-dimensionality simplex of $m$ individuals where $2 < m < D+1$. When $m=3$ the method is called the Triangle Evolution (TE) algorithm. In Luo et al. (2013), three techniques (namely, low-dimensional reproduction, normal struggle and variable dimension) have been used to improve the performance of LDSE. Low-dimensional reproduction allows LDSE to find the global optimum with a small population by replacing the linear reproduction operator with a nonlinear one. Normal struggle improves the local search ability of LDSE by adding a normal noise to the best individual of the $m$-simplex. Variable dimension makes better use of recent information by exploiting around the current simplex. However, the method of Luo et al. (2013) is complicated (e.g. concept of promising k-facets, variable dimension technique, etc.), not adaptive and has many parameters.

In this paper, a new Adaptive Population-based Simplex (APS) algorithm is proposed which is derived from the work of Luo et al. (2013). We mainly used two principles from that work:

- A population from which different simplexes are selected.
- Local search as a last chance to improve the classical NM method.

APS is an easy to use (no need to tune any parameter), easy to code (free MATLAB and C codes are available at (http://aps-optim.info) and robust approach.

Section 2 introduces the proposed approach. Section 3 discusses our experimental results. Finally, the paper concludes with Section 4.

2. APS DESCRIPTION

We started from the method proposed by Luo et al. (2013), but we significantly modified it, in order to have a tuning-free method, and nevertheless have good performances on a large range of dimensions (up to 100). We call our method tuning-free because we have assigned its parameters intuitive values that prove to be highly robust, yielding good results without modifying them for
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