SOMA-CLP for Competition on Bound Constrained Single Objective Numerical Optimization Benchmark

A competition entry on Bound Constrained Single Objective Numerical Optimization at The Genetic and Evolutionary Computation Conference (GECCO) 2021

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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) 2021 by a novel algorithm titled Self-organizing Migrating Algorithm with CLustering-aided migration and adaptive perturbation vector control (SOMA-CLP).

CCS CONCEPTS

• **Mathematics of computing → Evolutionary algorithms**.

KEYWORDS

SOMA, k-means, clustering, CEC 2021

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1 INTRODUCTION

This competition entry proposes an improved metaheuristic algorithm for global optimization titled Self-organizing Migrating Algorithm with CLustering-aided migration and adaptive Perturbation vector control (SOMA-CLP). The SOMA-CLP algorithm is a direct descendant of SOMA-CL [4]. Both algorithms can be classified as modern variants of the Self-Organizing Migrating Algorithm (SOMA). The SOMA [9] was initially developed in 1999 by I. Zelinka and later popularized in 2001, 2004 and mainly in 2019, when several new powerful versions [1, 2] have been introduced for the 100-digit challenge [6]. The workflow of the new proposed SOMA-CLP is given in the next section. Due to the strict limitation of the number of pages, complete results are available at the link in the result section.

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2 SOMA-CLP ALGORITHM

The SOMA-CLP represents the updated version of its predecessor SOMA-CL. SOMA-CLP uses a linear adaptation of the *prt* control parameter to generate a perturbation vector, promoting the global transition from the tendency of exploration to exploitation as the strength of perturbation of individuals' movement weakens.

The workflow of the SOMA-CLP can be divided into three phases. The first exploration phase is focused on space mapping. The second phase performs clustering of the mapped space by k-means method [3] and the third phase is focused on exploitation by performing a more detailed screening of areas of interest discovered during the first phase. All three phases thus define one iteration of the algorithm.

2.1 Exploration Phase

This phase uses the SOMA with All-To-Random strategy. An individual called "leader" is selected randomly from the population set of NP individuals for each migration of active individual $\boldsymbol{x}$. The migration process is defined by the equation (1).

$$x_{i,j}^{k+1} = x_{i,j}^{k} + \left(x_{L,j}^{k} - x_{i,j}^{k}\right) \cdot t \cdot PRTVector_j \tag{1}$$

Where the $x_{i,j}^{k+1}$ is a new position of an i-th individual in j-dimension for a next iteration step $k+1$. Accordingly, the $x_{i,j}^{k}$ is a position of the same individual in k iteration. The $x_{L,j}^{k}$ the position of a leader. Individual discrete steps between an i-th individual and selected leader $x_{L,j}^{k}$ are represented by t parameter. The best-found solution on this path is then transferred into a new iteration. The t parameter is a collection of values starting from 0 to $PathLength$ with increment (or step size) of $Step$. Each evaluated solution is stored in a memory $\boldsymbol{M}$. This memory $\boldsymbol{M}$ of all visited solutions is used in the next phase of the algorithm.

The $PRTVector_j$ mimics the mutation process and should be generated as (2) for all the individual t steps. This vector determines in which dimensions j the i-th individual will migrate towards a leader and which dimensions stay unchanged. The prt parameter can be considered as a threshold value and is chosen in the range from 0 to 1 of a uniform distribution.

$$PRTVector_j = \begin{cases} 1 & \text{, if}(rand_j < prt) \\ 0 & \text{, otherwise} \end{cases} \quad (2)$$

The main difference between SOMA (and SOMA-CL) and the proposed SOMA-CLP is the usage of the adaptive prt parameter similar as in other modern variants of SOMA [1, 2]. This adaptation, as in equation (3), affects the covered area by the exploration phase throughout the algorithm lifespan. The prt represents the strength of a mutation during the migration and starts with the low value (high mutation change – wider hyperspace of solutions between active individual and leader), and it is steadily increasing to an upper limit (low mutation change – "direct" path between active individual and leader).

$$prt = 0.08 + 0.9 \cdot (FES/maxFES) \quad (3)$$

Where the FES is the number of objective function evaluations in a given time, and the $maxFES$ is the maximal limit of such evaluations.

2.2 Clustering of the Mapped Space

The evaluated solutions stored in the memory $\boldsymbol{M}$ during the previous exploration phase are investigated in this second phase. Candidate leaders for the last exploitation phase are selected from the memory $\boldsymbol{M}$. The basic idea is to select only a few promising solutions from the whole covered hyperspace. Therefore, a clustering method to divide all solutions by their parameter values into several groups (clusters) is used. Namely, the k-means clustering method [5]. The number of outcome clusters should be 10% of the NP, or it may be set by the user as NP_L. From each of the created clusters, only solutions with the best objective function value within their cluster – so-called cluster leaders are selected.

2.3 Exploitation Phase

The leader $x_{L,j}$ in equation (1) is this time selected from the set of cluster leaders using the Rank Selection technique [8] Thus the solution with the best objective function value has the highest probability to be chosen as a leader, the second-best has the second-highest probability of being selected, and so on. The worst solution has the lowest chance to be chosen as a leader. New leader is selected for each individual. The individual x_i is again migrating by discrete steps, and the best-found solution on t-th position is propagated into a new iteration of the algorithm. The t parameter is generated in a range starting from 0 to $pathLength_L$ with step size $step_L$. The leader selection with parameters values of $pathLength_L$ and $step_L$ should ensure the exploitation of an promising solutions discovered in the previous phase. The $PRTVector_j$ is generated in the same way as in equation (2), and the prt is again computed by (3).

The described three phases of the SOMA-CLP are repeated until the stopping condition is met, typically the $maxFES$ is reached.

3 EXPERIMENTAL SETTING

The Special Session and Competition on Single Objective Bound Constrained Optimization [7] is accompanied by a technical report providing test function definitions and the evaluation criteria with a manual on measuring the time complexity of the benchmarked algorithm. The values of the control parameters for SOMA-CLP were following: NP=100, textitNP$_L$=10, $step$=0.33, $step_L$=0.11, $pathLength$=3.0, $pathLength_L$=2.0.

4 RESULTS

In this section, only the results for algorithm time complexity are provided in a format required by the benchmark suite (see Table. 1). The complete results are accessible online at the A.I.Lab website [1]. The source code of the SOMA-CLP is available at the A.I.Lab Github [2].

Table 1: Computational Complexity

	T0	T1	T2	T2 - T1/T0
10	1.09E−02	2.12E−01	1.40E+01	1.20E+03
20	1.09E−02	6.44E−01	2.60E+01	2.33E+03

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[1] https://ailab.fai.utb.cz/resources/

[2] https://github.com/TBU-AILab/SOMA_CLP