Investigating the Effects of Population Size and the Number of Subcomponents on the Performance of SHADE Algorithm with Random Adaptive Grouping for LSGO Problems

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ABSTRACT

Large-scale global optimization (LSGO) problems are known as hard problems for many evolutionary algorithms (EAs). LSGO problems are usually computationally costly, thus an experimental analysis for choosing an appropriate algorithm and its parameter settings is difficult or sometimes impossible. In this study, we have investigated the performance of novel EA for LSGO based on Adaptive Differential Evolution with Success-History (SHADE) and cooperative coevolution (CC) with random adaptive grouping (RAG). SHADE is a self-adaptive DE algorithm. RAG approach is able to identify effective combinations of variables (subcomponents) in the problem decomposition stage. Thus, the proposed approach contains only two controlled parameters: the population size and the number of subcomponents. We have evaluated the performance of CC-SHADE-RAG with different settings on the IEEE CEC LSGO benchmark. The experimental results show that the approach outperforms some state-of-the-art LSGO techniques. CC-SHADE-RAG performs better with a small number of subcomponents and large size of population. We have performed statistical analysis for the experimental results and have established that the population size has greater effect on the algorithm performance than the number of subcomponents. This information can be used for further development of a completely self-adaptive LSGO technique by introducing an adaptive population sizing scheme in CC-SHADE-RAG.

CCS CONCEPTS

• **Theory of computation → Evolutionary algorithms;** • **Computing methodologies → Search methodologies**

KEYWORDS

Large scale global optimization, differential evolution, problem decomposition, cooperative coevolution

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1 INTRODUCTION

In recent years, many real-world optimization problems have had to deal with growing dimensionality. The performance of EAs usually decreases when the dimensionality of the search space increases. There exist many LSGO techniques and the best results and the majority of approaches are presented by CC methods. In [1] a new grouping method (Random Adaptive Grouping, RAG) is proposed. The RAG combined with differential evolution (DE) has demonstrated the performance comparable with some state-of-the-art LSGO methods. In this study, we have applied Adaptive Differential Evolution with Success-History [2] as the core optimization technique for CC framework with RAG. SHADE is a self-adaptive algorithm and it has only one controlled parameter that can correlate with the dimensionality of optimization problems after decomposition – the population size. We have evaluated the performance of the proposed CC-SHADE-RAG with different combinations of the chosen controlled parameters on the IEEE CEC 2010 LSGO benchmark. We have applied the two-way Analysis of Variance (ANOVA) for establishing which parameter has greater effect on the algorithm performance, and, finally, we have compared CC-SHADE-RAG with the best-found parameters with some state-of-the-art LSGO techniques.

2 EXPERIMENTAL RESULTS

In this study, we have used all experimental setups as in the IEEE CEC 2010 LSGO Competition rules. The performance of CC-SHADE-RAG has been estimated using all combinations of the following values of controlled parameters: the number of subcomponents (M) is 4, 8, 10, 20, 40, 50 and 100, the size of population (pop_size) is 25, 50, 75, 100, 125, 150, 175 and 200.

Table 1 presents the results of evaluation of R-squared for different data sets. The table also contains p-values obtained by the two-way ANOVA. As we can see in Table 1, p-values for F-statistics are lower (better) for the population size parameter, except the first row when R- squared is the lowest. We can conclude that the best performance for CC-SHADE-RAG is achieved with small values of M in the narrow range, and the size of population has greater effect on the algorithm performance. From the practical point of view, a fine-tuning the population size with a fixed small value of M is more preferable.

Table 1: The coefficient of determination and ANOVA results for different data sets

M	R-squared	ANOVA	
		p-value for M	p-value for *pop_size*
4, 8, 10, 20, 40, 50, 100	0,5521	0,0000941	0,0726
4, 8, 10, 20, 40, 50	0,5823	0,00308	0,00363
4, 8, 10, 20, 40	0,6695	0,018961	0,000221
4, 8, 10, 20	0,8723	0,0139	0,000000113
4, 8, 10	0,9739	0,00002	0,00000000106
4, 8	0,9752	0,00137	0,0000595

We have compared the results obtained with the best settings for each M from the set {4, 8, 10, 20, 40}, have ranked algorithms for each benchmark function and then have evaluated the benchmark-average ranks. The results are presented in Fig. 1. We have applied the Wilcoxon-Mann-Whitney test ($p<0.05$) for checking if there statistically significant difference in the results. The maximum number of problems where the difference in the results is not significant among all pair comparisons is equal to 5 (from 20 problem).

We have analyzed the convergence graphs for the best CC-SHADE-RAG configurations. Algorithms with the best-found population size demonstrate almost similar convergence for different numbers of subcomponents.

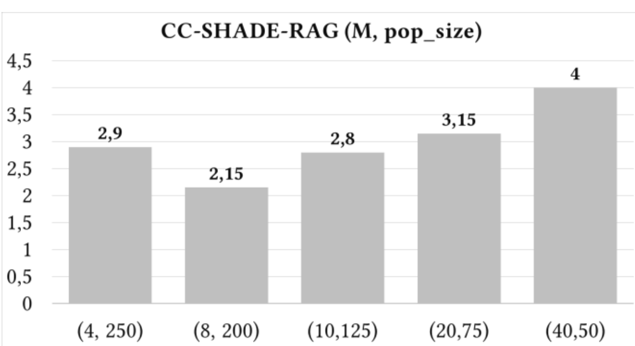

Figure 1: The average ranks for the best CC-SHADE-RAG configurations.

Finally, we will compare the best-found configuration CC-SHADE-RAG(8,200) with some state-of-the-art LSGO methods. After we have analyzed and compared all experimental results, we have ranked algorithms. The final ranking of all algorithms is presented in Fig. 2.

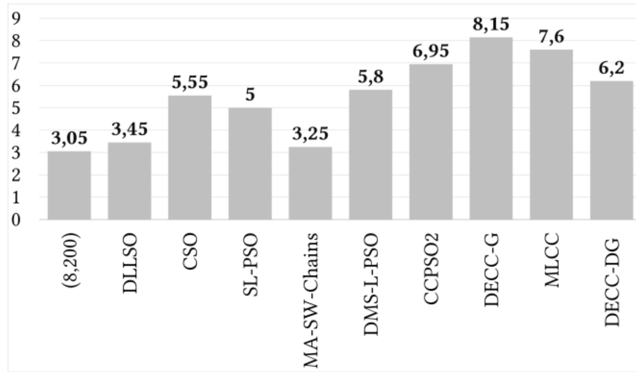

Figure 2: The average ranks for LSGO algorithms.

As we can see, the proposed CC-SHADE-RAG outperforms all compared algorithms. It should also be noted, that the MA-SW-Chains algorithm is the winner of the IEEE CEC 2010 LSGO competition.

3 CONCLUSIONS

In this study, we have proposed a novel LSGO algorithm titled CC-SHADE-RAG. We have investigated its performance with the CEC 2010 LSGO benchmark and have discovered using the ANOVA that the population size is the more important parameter that has greater effect of the algorithm performance while the number of subcomponents can be defined in a narrow range of small values. We have also demonstrated that the convergence of CC-SHADE-RAG with the fine-tuned population size is almost not sensitive to settings of the number of subcomponents.

The proposed approach and the conclusions on its performance can be used for solving real-world BB LSGO problems with the limited budget of fitness evaluations.

In further work, we will introduce a self-adaptation of the population size in order to develop a completely self-adaptive LSGO technique. In addition, more detailed analysis of the approach will be provided using alternative benchmarks.

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