A New Grouping Strategy-Based Hybrid Algorithm for Large Scale Global Optimization Problems

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ABSTRACT

Large scale global optimization (LSGO) problems are a kind of very challenging problems due to their high nonlinearity, high dimensionality and too many local optimal solutions. The variable grouping strategies including black-box grouping strategies and white-box grouping strategy are the most hopeful strategies which can decompose a large scale problem into several smaller scale sub-problems and make the problem solving become easier. In this paper, we first propose a new variable grouping strategy which can be applicable to fully non-separable LSGO problems. Then, a new line search method is designed which can make a quick scan to arrive in promising regions and help the new variable grouping strategy to divide the LSGO problem properly. Furthermore, a differential evolutionary (DE) algorithm with a new mutation strategy is designed. Combining all these, a new hybrid algorithm for LSGO problems is proposed.

CCS CONCEPTS

•Theory of computation → Bio-inspired optimization;

ACM Reference format:
Haiyan Liu, Yuping Wang *, Liwen Liu, Xiao-Zhi Gao, and Yiu-ming Cheung. 2017. A New Grouping Strategy-Based Hybrid Algorithm for Large Scale Global Optimization Problems. In *Proceedings of GECCO '17 Companion, Berlin, Germany, July 15-19, 2017,* 2 pages.
DOI: http://dx.doi.org/10.1145/3067695.3075978

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1 IMPROVED CONTRIBUTION BASED GROUPING STRATEGY (ICBG FOR SHORT)

1) Use a new line search method to make the search and record the improvement along each dimension.
Suppose the search region of dimension x_i is $[lb(i), ub(i)]$ where $ub(i)$ and $lb(i)$ are the upper and lower bounds of variable x_i, respectively. To do the line search for dimension x_i, we uniformly insert *popsize* points including the upper and lower bounds into $[lb(i), ub(i)]$, where *popsize* is the population size. These points are called levels of dimension x_i and the search region $[lb(i), ub(i)]$ is equally divided into $(popsize - 1)$ sub-intervals by these points. Then we evaluate each level along dimension x_i and record the best level as x_i^* for $i = 1, \cdots n$. In this way, we can record the improvement along each dimension. To further focus the search, we reset the upper and lower bounds of the search region to $lb(i) = x_i^* - d$ and $ub(i) = x_i^* + d$ respectively where d is the distance between the best level x_i^* and the middle level of dimension x_i.

2) The components of x with the similar improvements are put into a group and this group corresponds to a sub-problem, i.e., the components of x in this group make up the variables of this sub-problem and the components not in this group are seen as constants in this sub-problem.

2 FRAMEWORK OF THE PROPOSED ALGORITHM

1) Decompose the LSGO problem considered into several smaller scale sub-problems.
Use FBG [2, 3] to decompose the LSGO problem into several smaller scale sub-problems when the LSGO problem is a fully separable or a partially separable, use ICBG to decompose the LSGO problem into several smaller scale sub-problems when the LSGO problem is a fully non-separable.
2) Optimize each sub-problem.

Use a local search method to optimize each sub-problem.
For fully separable problems (e.g. $f1 - f3$) we only use the proposed line search method till the maximum function evaluations are met. For other problems, we use the Matlab fmincon function as the local search method.
3) Use the proposed DE algorithm to further optimize the problem.
The new differential evolution algorithm use the following mutation strategy:

$$x(index) = x_{best}(index) + \lambda * (x_{best}(index) - x_{prebest}(index));$$

where $index$ is the set containing the indices of variables of the specific groups, x_{best} is current best point obtained from the optimization of each sub component, $x_{prebest}$ is the previous best point and λ is the step size. Initially, we set $\lambda = rand * max(ubound - lbound)/[max(x_{best} - x_{prebest})20]$. Afterwards, λ will be increased by $\lambda = \lambda * 2$ each time when the improvement on this group is enough.
4) Repeat above steps until the stopping criterion is met.

3 EXPERIMENTS

The experiments are conducted on the most challenging problems, i.e., CEC' 2013 benchmark suite for LSGO problems. The proposed algorithm is compared with the state-of-the art algorithm MOS [1] which is the best performance algorithm for LSGO problems on CEC'2013 benchmark suite until now. The best, mean, median, worst, standard deviation values are recorded. The paired-sample t-test is conducted at a significant level $\alpha = 0.01$ and the p-value of the t-tests are recorded.

The experiment results show the proposed algorithm has 7 wins, 7 defeats and 1 tie with MOS. It seems that it has similar performance with MOS, however, by careful analysis, the proposed algorithm performs better than MOS. Due to the page limits, we only demonstrate the results of two problems for each kind of fully separable problems ($f2, f3$), partially separable problems($f7, f11$) and fully non-separable problems($f12, f15$), respectively. The results are summarized in Table 1. For all functions except for $f2$, the results obtained by the proposed algorithm are better than those obtained by MOS. Also, for three functions $f7, f11$ and $f12$, the solutions obtained by the proposed algorithm are close to the true optimal solutions, while only for function $f2$, the solution obtained by MOS is close to true optimal solution. This indicates the proposed algorithm is more efficient.

Table 1: Comparison between the new algorithm and MOS on CEC' 2013 benchmark suite

P		New Algorithm	MOS	p-value
f2	Best	**8.93e+01**	7.40e+02	8.14e-31
	Median	**8.93e+01**	8.36e+02	
	Worst	**8.93e+01**	9.28e+02	
	Mean	**8.93e+01**	8.32e+02	
	Std	**0.00e+00**	4.48e+01	
f3	Best	2.00e+01	**8.20e-13**	9.64e-32
	Median	2.00e+01	**9.10e-13**	
	Worst	2.00e+01	**1.00e-12**	
	Mean	2.00e+01	**9.17e-13**	
	Std	**3.74e-15**	5.23e-14	
f7	Best	**1.17e-04**	3.49e+03	4.99e-05
	Median	**1.49e-04**	1.62e+04	
	Worst	**3.18e-04**	3.73e+04	
	Mean	**1.68e-04**	1.62e+04	
	Std	**6.94e-05**	9.29e+03	
f11	Best	**3.09e-02**	2.06e+07	2.16e-04
	Median	**1.65e+00**	4.48e+07	
	Worst	**3.25e+00**	9.50e+07	
	Mean	**1.65e+00**	5.22e+07	
	Std	**1.72e+00**	2.10e+07	
f12	Best	**1.14e-07**	2.22e-01	2.00e-3
	Median	**1.20e-07**	2.46e+02	
	Worst	**1.30e-07**	1.17e+03	
	Mean	**1.21e-07**	2.47e+02	
	Std	**5.18e-09**	2.59e+02	
f15	Best	**4.82e+04**	2.03e+06	2.33e-13
	Median	**1.33e+05**	2.38e+06	
	Worst	**2.36e+05**	2.88e+06	
	Mean	**1.40e+05**	2.35e+06	
	Std	**5.46e+04**	1.98e+05	

4 CONCLUSION

In this paper we propose a new grouping strategy for fully non-separable large scale problems in order to decompose the large scale problem into small scale sub problems. In order to fulfill the decomposition as well as to save computational resources, we design a line search method to make a rough and quick scan over the whole search space and use the improvement of the line search on each dimension to construct the new grouping strategy. Also, a new DE algorithm with a new mutation strategy is proposed as the optimizer for each sub group. Combining all these, a hybrid algorithm for solving large scale optimization problem is proposed. Numerical experiment results show that the proposed algorithm is of great potentials and more efficient than the best existing algorithm MOS. The results also indicate that the proposed algorithm can obtain good solutions with the precision $e - 4$ for three problems and acceptable solutions with the precision $e + 1$ for five problems, which is the current best results. Also, the proposed algorithm improves the worst result from $8e+12$ of MOS to $8e + 9$ which is also a big progress.

5 ACKNOWLEDGMENT

This work was supported by National Natural Science Foundation of China (No. 61472297, U1404622 and 61672444) and the SZSTI Grant (JCYJ20160531194006833).

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