Adaptive Grammatical Evolution in a Particle Swarm Optimisation Setting

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Abstract

A customised particle swarm optimiser was developed by incorporating adaptive building blocks into grammatical evolution. As a result, the algorithm can self-adapt to different problem instances. By scoring the building blocks, we are seeking to provide the means of generating novel population-based meta-heuristics automatically. With our new self-adapting algorithm, we propose a novel way to reduce computational time and iteration count by adaptively selecting and scoring building blocks. To attain our objective, we extracted building blocks from a wide range of existing particle swam optimisers and scored them during the evolutionary process. In cases where evolved solutions failed to improve the overall fitness, these scores were provided to the evolutionary process as input into the evolutionary process. We demonstrated numerically that the proposed adaptive building blocks algorithm used in the proposed algorithm reduced the computation time as well as the iteration count compared to PSO.

Preliminary Works

- ❖ The basic building blocks (BBs) are the sets of rules or processes involved in the process of building the search algorithm.
- ❖ In order to improve the PSO and evolutionary algorithm, researchers have used a variety of BBs and implemented various strategies.
- ❖ Parameter tuning and parameter control are the two types of BBs settings in the literature of evolutionary algorithms.

Grammatical Evolution with Adaptive Building Blocks (GEABB) Framework

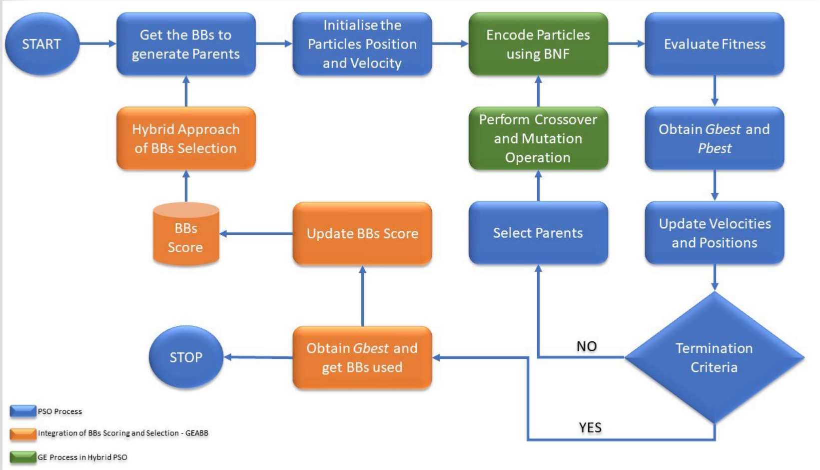

Fig 1: Integration of GE with PSO for providing adaptive BBs. The bright orange blocks in the flowchart represent the new elements introduced in our novel GEABB framework.

CEC'2013 Benchmark Functions

The Following properties describe the multimodal test functions (*Li et al. 2013*):

- ❖ F1, F2, F3 are 1D multimodal test functions. F4, F5 are 2D multimodal test functions which are not scalable.
- ❖ F6-F8 are the scalable multimodal functions. The ***global optima*** of F6 and F7 are determined by the dimension *D.* In contrast, F8's global optima are independent of D, therefore, they can be customised.
- ❖ F9-F12 are scalable multimodal functions that are constructed of several basic functions with different properties which can be customised by the user.

Performance Analysis

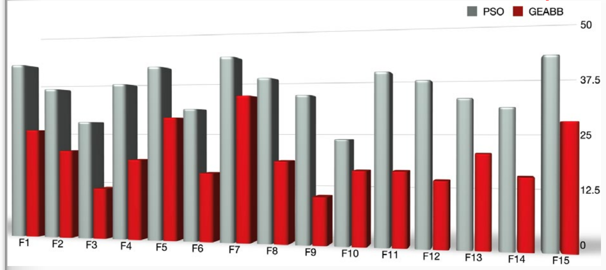

Fig 2: Comparison of iteration count between PSO and GEABB with CEC'2013 benchmark functions. The shorter bar length indicates the better efficiency of the algorithm as it takes less iterations in finding optimal fitness, such as in the cases of F3 and F9.

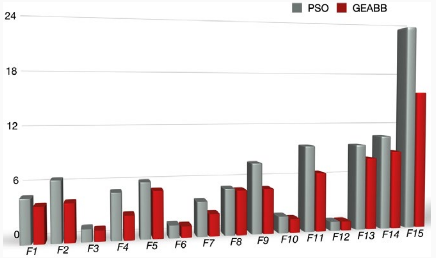

Fig 3: The comparison of mean run time (in seconds) of PSO and GEABB with CEC'2013 benchmark functions. The shorter bar length indicates less computational time, thus more computationally efficient algorithm.

Conclusion

- ❖ GEABB, a novel approach with scoring and recommending BBs is presented to find the optimal solution by adapting the algorithm to the problem instance.
- ❖ Adaptive BBs solutions are provided with a hybrid approach without requiring any manual interpretations to the blocks set.
- ❖ For all benchmark problems tested, GEABB outperforms the PSO by taking fewer iterations and taking less computation time.

References

- ❑ Li, X., Tang, K., Omidvar, M., Yang, Z., Qin, K., & China, H. (2013). Benchmark functions for the CEC'2013 special session and competition on large-scale global optimization. Gene, 7(33), 8.
- ❑ Sengupta, S., Basak, S., & Peters, R. (2018). Particle Swarm Optimization: A Survey of Historical and Recent Developments with Hybridization Perspectives. Machine Learning and Knowledge Extraction, 1(1), 157–191. https://doi.org/10.3390/make1010010

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