Event-driven multi-population optimization: mixing Swarm and Evolutionary strategies

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ABSTRACT

Recently, in the field of nature-inspired optimization, researchers have proposed multi-population asynchronous algorithms that distribute the evolutionary process among heterogeneous seach paradigms.These algorithms execute the seach strategy by taking streams of populations from message queues, and replacing them with evolved populations. Moreover, current studies suggest that having a high number of populations interacting in parallel, the effect of the individual parameters of each population is compensated by those selected in other populations improving the performance of the algorithm. In this work, we propose a simple reactive migration method for the asynchronous execution of multi-population, multi-strategy algorithms that improves over homogeneous configurations. We evaluate this method by comparing between homogeneous and an ensemble of multi-populations, using Genetic Algorithms (GAs) and Particle Swarm Optimization (PSO) in the noisless BBOB testbed for the optimization of continuous functions. Results show, that this method offers better performance, even when compared with other asynchronous population based algorithms.

CCS CONCEPTS

• **Computer systems organization → Embedded systems**; *Redundancy*; Robotics; • **Networks** → Network reliability;

KEYWORDS

ACM proceedings, LaTeX, text tagging

ACM Reference Format:
ANONYMOUS and ANONYMOUS ANONYMOUS. 2020. Event-driven multi-population optimization: mixing Swarm and Evolutionary strategies. In *Proceedings of the Genetic and Evolutionary Computation Conference 2020 (GECCO '20).* ACM, New York, NY, USA, 3 pages. https://doi.org/10.1145/nnnnnnn.nnnnnnn

1 INTRODUCTION

Nature-inspired optimization algorithms have been used successfully in the last decades to tackle complex problems [18]. Algorithms taking inspiration in nature include evolutionary algorithms (EAs) [2] and swarm intelligence (SI) [10]. A common characteristic of these two methods is the use of an initial set of random candidate solutions that are manipulated by the algorithm to generate a new set of candidates, and because of this, we commonly referred to them as population-based algorithms. Popular EAs are Genetic Algorithms (GAs) [5, 8], and Differential Evolution (DE) [9]. While examples of (SI) [10] are particle swarm optimization (PSO) [3], and ant colony algorithms (ACO) [4].

A drawback of population-based algorithms is that they can be computationally expensive, and that is why researchers have been proposing some form of parallelization [14] to increase the scalability of these algorithms. One of the first methods of parallelization was the island model, which lead to an increased performance [6, 7]. The concept was to divide the population into smaller populations that communicated with each other. Other population-based algorithms have adopted the technique, and since then, researchers have found additional advantages besides the execution speed; these include avoiding a premature convergence and maintaining the diversity of the global population [11]. Some researchers use the term multi-population based methods when referring to techniques using many populations as part of their optimization strategy [13]. The relative isolation in which populations carry out the algorithm, together with the synchronous or asynchronous communication, helps to increase the overall diversity since each population will search in a particular area, at least between communications. Multi-population algorithms mainly use a form of communication to recombine or migrate candidate solutions between populations to avoid premature convergence, since smaller populations are known to perform better for a given problem than bigger populations [12, 17]. In some cases, a multi-population based algorithm scales better due to the interactions b and the parallelism of the operation [1].

Several multi-population based are heterogeneous, integrating various optimization algorithms, and often perform better than single-population or homogeneous optimization algorithms [15, 17]. Heterogeneous algorithms add to the problem of finding the correct parameter settings for each population; because some parameters affect the accuracy of the solution and the convergence speed of the individual algorithms as they tip the balance between exploration and exploitation of the search space. On the other hand, current studies show that by having a high number of populations communicating in parallel, the effect of the individual parameters of each population is compensated by those selected in other populations [12, 16]. Some level of heterogeneity can be implemented by just changing the configuration parameters of each population,

*Dr. ANONYMOUS insisted his name be first.

GECCO '20, July 8–12, 2020, Cancun, Mexico

ACM ISBN 978-x-xxxx-xxxx-x/YY/MM…$15.00
https://doi.org/10.1145/nnnnnnn.nnnnnnn

Table 1: DEAP GA EvoWorker Parameters

Selection	Tournament size=12
Mutation	Gaussian $\mu = 0.0$, $\sigma = 0.5$, indbp=0.05
Mutation Probability	[0.1,0.3]
Crossover	Two Point
Crossover Probability	[0.2,0.6]

Table 2: EvoloPy PSO Parameters

V_{max}	6
W_{max}	0.9
W_{min}	0.2
C_1	2
C_2	2

Table 3: Parameters used in the experiments with ten populations

Dimension	2	3	5	10	20	40
Generations	40	25	28	50	66	80
Population Size	50	60	60	70	100	125
Populations	10	10	10	10	10	10
Iterations	10	20	30	30	30	40

but in this case, we are interested in heterogeneous search strategies. Therefore, in this paper, we compare heterogeneous multi-populations with only a GA or PSO search strategy in populations, versus an ensemble multi-population of GA and PSO algorithms. As a benchmark, we used the first five functions of the BBOB testbed.

2 STATE OF THE ART

3 PROPOSED METHOD

4 SETUP

ACKNOWLEDGMENTS

The authors would also like to thank the anonymous referees for their valuable comments and helpful suggestions. The work is supported by the

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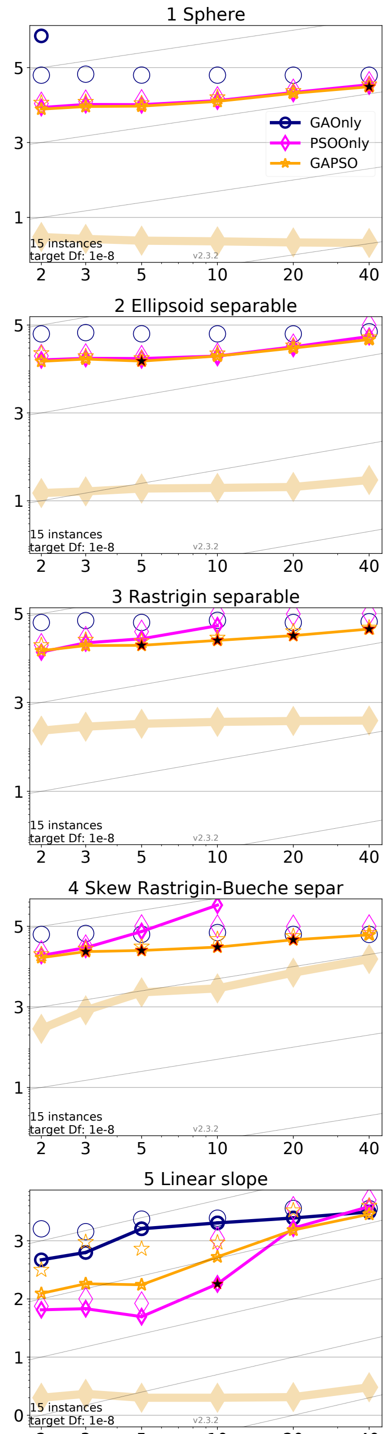

Figure 1: Average running time (in #FEs as log_{10} value), divided by dimension for target function value 10^{-8} vs dimension. Algorithms legends are given in f_1. Light symbols give the maximum number of function evaluations from the longest trial divided by dimension. Black stars indicate a statistically better result compared to all other algorithms ($p < 0.01$) and Bonferroni correction number of dimensions (six).