FREE SEARCH – A NOVEL HEURISTIC METHOD

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Key words to describe the work: Evolutionary computing, Artificial Intelligence, Free Search.

Key Results: Inspired from the nature new population-based algorithm applied to numerical optimisation.

How does the work advance the state-of-the-art?: Novel approach to stochastic processes. Reflects on an improvement of the optimisation effectiveness and robustness. Benefits optimisation and nature understanding

Motivation (problems addressed): An improvement of optimisation process in terms of better performance and robustness, which can support wide range disciplines, we consider as a challenge for research.

Introduction

Our research focuses on adaptive population-based heuristic search methods applied to numerical optimisation. In fact, evolutionary computing is largely a family of population-based algorithms [4]. We explored several population-based algorithms and abstracted their common features. Having identified these features we designed the concept and the architecture of a new heuristic search. It was implemented as an algorithm, which we called Free Search (FS). This paper reviews the behaviour of different population-based optimisation methods applied to numerical test problem. We focus on Genetic Algorithm (GA)[5], Particle Swarm Optimisation (PSO)[3], Differential evolution (DE)[6], Ant Colony Optimisation (ACO) [2] and - newly proposed and implemented by us - Free Search (FS). The aim is to assess FS robustness and effectiveness in comparison with other existing population-based algorithms.

Illustrative optimisation problem

Maximise a multi-modal (m) multi-dimensional (n) test function for limited number of iterations g:

$$f(x_i) = \sum_{j=1}^{m} \{ z_j / [1 + k_j * \sum_{i=1}^{n} (a_{ji} - x_i)^2] \}, \; j=1,..,m \quad i=1,..,n$$

This function defines continuous search space. All four methods are able to cope with it. The results give a base for comparison and assessment of the methods robustness. The ability of the optimisation methods to achieve successful results we are calling robustness. One method is low robust if it produces low number successful results or it is robust if it produces high number successful results, for a limited period and limited computational resources.
The test function was implemented in two variants:
- easy variant with wide smooth global maximum in the middle of the search space and hard variant with thin sharp global maximum near to the border of the search space.

Free Search – essential properties

FS is a new population-based search heuristic, inspired from the animals' behaviour. FS can be applied to real value numerical optimisation problems, as well as GA, DE and PSO [1]. There is, however, difference and an advantage, in comparison to ACO [2], which is meta-heuristic, applied to the discrete optimisation problems.
FS works as follows. It has a population of S animals. They can move step by step (discrete movement) through D dimensional non-discrete search space. Each animal makes exploration journeys. The aim of the journeys is to find a favour (a better satisfaction of an objective function). The journeys are for a determinate period (number of steps). The first journey starts from a random or certain (for example the middle) location within the search space. The directions for a first journey are random. During the journey each animal achieves some favour F (an objective function solution) and distributes a pheromone FM in amount proportional to the favour (the objective function satisfaction) found during the journey. After each journey the pheromone is fully replaced with a new one.
Each animal has a sense for pheromone U. By the level of this sense U the animal checks the space for a pheromone FM and selects the direction for search, which suit its sense. The sense is our conceptual improvement of population-based optimisation algorithms. It has no analogue in DE, PSO and ACO. The sense is a tool for regulation of the divergence and the convergence within the search process and a tool for guiding of the space exploration. During the journey animals make steps in the neighbouring space to the limited size R. The neighbouring space is a tool for tuning of rough and precise searches. The concept for a neighbouring space corresponds to the concept of neighbour nodes in ACO. The difference is that in ACO, neighbour nodes are discrete locations and neighbouring space in FS is continuous area

appropriate for numerical optimisation. The animal in FS can explore in any direction, no matter, whether this is the direction of the best own solution found, or the best solution found from another animal, or the best solution found from all the population. By increasing the U the animal can be forced to search to the direction of the best-found solution from all animals – local search. By decreasing the U, the animal can be allowed to explore directions found from other animals but not the best for the population – global exploration. In FS the sense U, the step limit R and the pheromone trail FM are subject of adaptive self-regulation, during the stochastic search process, on random principle. In FS we relate the sense and the action, which we consider as a basis of artificial thinking.
These abilities of the FS deserve attention and investigation with wide range test problems.

Illustrative experimental results

A short summary of the results is presented - easy variant on Figure 1., and - hard variant on Figure 2. For all tests population has 10 individuals, 320 experiments per method, m=3 (3 maxima) and n=5 (5 dimensions). On the figures we present the number of achieved successful results per 100, 1000 and 2000 generations (g) for GA, PSO, DE and FS. We accept a result as successful if the average value of the objective function for the population is higher than the values of all local maxima. It means: it is in the global maximum area and can be near or equal to the global maximum.

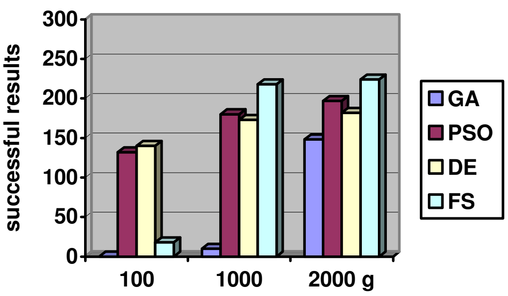

Figure 1. Successful results easy variant

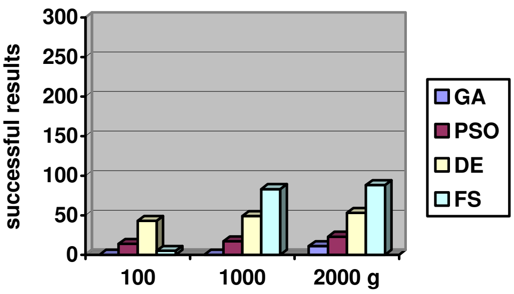

Figure 2. Successful results hard variant

For the easy variant PSO and DE reach the global maximum in first 100 iterations for ~40% of the experiments. After 2000 iterations the global maximum is reached by ~50%. For the hard variant results are: for PSO ~5% to ~10% and for DE ~10% to ~15%. For PSO and DE is difficult to avoid local maximum if the populations fall in it, in the beginning of the optimisation. The behaviour of GA and FS is different. For the easy variant in the beginning (in first 100 iterations) around ~5% of the tasks FS reaches the global maximum but after 1000 and 2000 iterations we have ~60% and ~70% successful results. For the hard variant we have 2% for 100 iterations and ~30% for 2000 iterations. GA has low convergence but avoids better trapping in local optima. Let us note that given assessment has qualitative, probabilistic nature.
In summary the experimental results suggest that: (1) on the initial stage DE and PSO have fast convergence to the optimum than FS; (2) FS has fast convergence to the optimum than GA; (3) FS better avoids trap in local maxima than DE and PSO consequently FS is robust than DE and PSO. Comparison, of FS and GA for robustness, needs additional large period experiments. Roughly the place of FS is between DE & PSO (which are faster but less robust) and GA (which has slow convergence). More general conclusions need additional experiments with wide range test problems.

Conclusion

A new population-based heuristic method is presented. It is an illustration of a new concept, which gives a robust algorithm applied to numerical optimisation. FS builds a new understanding of stochastic processes and optimisation. It demonstrates promising results and has potential for improvement. For further research we propose comprehensive analysis and experimental study, which may lead to the FS robustness and convergence speed improvement.

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