Coursework 2 - Implementing and Comparing Genetic Algorithm and Particle Swarm Optimisation

F21BC: Biologically Inspired Computation

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# Introduction

The task was to implement Genetic Algorithm (GA) and Particle Swarm Optimisation (PSO) optimization algorithms from scratch and to carry out some experiments to see how they compare when evaluated on the CEC 2005 test functions (Suganthan et al., 2005). These test functions are used to assess optimization functions on an artificial landscape. The goal of the optimization algorithms was the find the global minimum (optimum value) in these test functions.

# Implementation

The implementations were based on the pseudocode from Luke (2016). The logic for the algorithms can be found in GA.py and PSO.py.

The following test functions were picked to test the algorithms with the following properties in mind:

* F2: Shifted Schwefel’s Problem 1.2
* F4: Shifted Schwefel’s Problem 1.2 with Noise in Fitness
* F8: Shifted Rotated Ackley’s Function with Global Optimum on Bounds
* F13: Shifted Expanded Griewank’s plus Rosenbrock’s Function (F8F2)
* F17: Rotated Version of Hybrid Composition Function with Noise in Fitness
* F24: Rotated Hybrid Composition Function

The aim was to cover a lot of different types of properties. F2 and F4 are both unimodal, without and with noise. All the rest are multi-modal. F8 is a single function, F13 is an expanded function and F17 and F24 are composite. F17 has a Gaussian noise in its fitness and for this reason, this is in-deterministic. All the other functions are deterministic. F17 and F24 are composite and due to the nature of the function, it has a lot of spikes in their artificial landscape which results in a high number of local optima. F8 has its local optima on its bounds.

## Genetic Algorithm

The genetic algorithm was implemented with elitism (Luke, 2016, pp. 46-47.). The code follows the same structure as the pseudocode, however, it had to be tweaked to allow multiple elites. The pseudocode’s line 10-11 is responsible for saving the best results after assessing the fitness. This was implemented differentially by using Python’s inbuilt sorting functions.

The algorithm has the option to use decreasing mutation rate. The program slowly decreases the mutation rate per generation if this is used. I.e. if the mutation rate is 80% then for the first generation the rate is unchanged, at half-point it's halved for 40% and the last generation is near 0%. The advantage of using decreasing mutation rate is to have a high mutation rate at the beginning which helps the algorithm to explore the artificial landscape and also avoid local optimums but narrows down the randomness as it progresses forward which helps to focus on attired solutions towards the last generations without scrambling it with high mutation.

Tournament selection is used with adjustable tournament size, 2 on default as per Luke (2016, pp. 45.).

Crossover percentage can be defined as well, this parameter gives the probability of crossover happening between parents. By default, it is 95%.

## Particle Swarm Optimisation

TEXT GOES HERE

I wrote about the stuff that I implemented as extra for GA. Don’t need to be too specific

# Results

The execution and analysis of the optimization functions can be found in the GA\_notebook.ipynb and PSO\_notebook.ipynb notebooks. We strongly recommend reading through the notebooks as those contain all our results analysed and explained.

The Genetic Algorithm was run in two iterations. First, we explored how GA evaluates a set of configurations using only lower numbers of generations. The optimizer performed the best on F8 and F13.

Each test function achieved the best score using 150 generations which was the maximum in the first iteration, so we decided to increase the number of generations to see how they improve. For the 2nd iteration, we kept the configuration of the best settings per test function. Each test function has two best scores. Best fitness and best average fitness.

Overall, the algorithm improved by increasing the number of generations and size of the population. The greatest improvement happened on the first two uni-modal functions (F2, F4). For the 2nd iteration, there was a notable improvement in the extended multimodal function (F13). However, on this function, the optimizer did well already in the 1st iteration and the change wasn’t as enormous as it was for the two uni-modal functions. The single function (F8) didn’t improve for the 2nd iteration, the best fitness on this test function did decrease slightly. The algorithm achieved a similar result as it did with the lower generation number in the 1st iteration, which implies that we found a good solution with a low error rate and low generations. The composite functions (F17, F24) did improve too, but their error was too high, with these configurations GA couldn’t a suitable solution for the test function. The high number of local optima that these composite functions have suggests that the optimizer algorithm got stuck in a local optimum. This can be avoided by increasing the population number.

<Barth: WRITE DOWN BRIEFLY YOUR RESULTS, NO NEED TO BE TOO SPECIFIC, PLEASE READ MINE ABOVE AND SEE WHERE YOU CAN REFERE TO IT

MY MAIN FINDINGS:

* F2 and F4 improved greatly with increasing the generation and population numbers.
* F8 Didn’t improve for the 2nd iteration, slightly worsend. This was the 2nd best in the first and 2nd iteration
* F13 did improve, not as much as F2 and F4 but it did. The fitness in both iterations
* F17 F24 got did improve too but error was too high even after the 2nd iteration. I assume that the algorithm got stuck in a local minimum.

WE NEED YOUR CONCLUSION BEFORE WE COMPARE.

>

# Discussion and Conclusions

DsSOME BULLSHIT HEREadasd

# References

Luke, S. (2016). *Essentials of Metaheuristics.* 2.3 ed. [online] Lulu, pp.31–58. Available at: https://cs.gmu.edu/~sean/book/metaheuristics/ [Accessed 27 Nov. 2022].

Suganthan, P., Hansen, N., Liang, J., Deb, K., Chen, Y., Auger, A. and Tiwari, S. (2005). Problem Definitions and Evaluation Criteria for the CEC 2005 Special Session on RealParameter Optimization. *Natural Computing*, 341-357.