COSC 3P71 PSO Report

Danny Nguyen

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1 Abstraction

This report demonstrates the vanilla particle swarm optimization functionalities and the results of using different parameters. This report also collect and analyze data between PSO that using parameters and random search.

2 Introduction

Particle Swarm Optimization (PSO) is an optimization algorithm that reconstructs the behaviour of a group of animals that are searching for a food source. By having individuals scatter throughout the area, the groups of individuals then start moving toward the desired location in the area, one by one. Birds, ants and fish are the prime examples of this algorithm. In this experiment, I use the vanilla PSO algorithm that are provided in class. Along with the PSO is the Rastrigin function that acts as the fitness function to determine the position that the particles are in. The implementation of random search is also included to provide results in order to compare the effectiveness between the impacts between parameters and random search on the final result.

3 Experiment Setup

The parameters that are used in the PSO algorithm are inertia, cognitive and social information. For these parameters, I use the provided values in the assignment.

1/ inertia: 0.729844, c1=c2= 1.496180

2/ inertia: 0.4, c1=c2= 1.2

3/ inertia: 1.0, c1=c2= 2.0

4/ inertia: -1.0, c1=c2= 2.0

The inertia value determines how much impact the previous velocity can have on the new velocity. In terms of value, higher inertia value leads to higher velocity which means the particle will move further away from its previous position. Also, lower inertia value means the particle will not move much from its previous position and it may need more iterations to reach the final destination.

The cognitive and social values are set to be the same value, which indicates that the particles would evaluate its personal best position and the global best position at the same priority. What cognitive information does is that the particle tends to move to its personal best positions rather than to global best. While social information means that the particles would move toward where the best particle is.

I use the suggested number of

particles as 30 and 1000 generations/iterations. The reason that I choose the iterations to be 1000 is because for some seeds, it takes more time to improve and to ensure all are evaluated equally, I decide to go with 1000 iterations. The range is between [-5.12, 5.12] as provided in the assignment. And the seeds that I use are from 1 to 5.

4 Result

With the parameter 1, the particles improve their positions from the start to the end and has the best final result compared to other parameters. The global best has a steady start in the beginning and reach the lowest the value. Once the global best reaches the low value, it keeps decreasing but slowly. The growth of parameter 1 is the best representation of PSO algorithm as the swarm gets better in each generation.

For parameter 2, the global best improves rapidly in the first several iterations then stop at a certain threshold. However, the final fitness value is the best when compared to parameter 1, but still better than parameter 3, 4 and random search. The reason for this threshold might be the low inertia value, which is 0.4. The lower inertia prevents particles from making any progress toward the goal as it only allows little movement to be made.

For parameter 3 and 4, both have identical results, which indicates negative or positve values on inertia parameter does not have any effect on the result. Also, the graph that both parameter 3 and 4 produce the worst final result, even worse than random search. The global particle does not move at all except for the first iteration, but it isn't significant. The exceptionally high cognitive and social information might be the caused as we can see from parameter 1 and 2.

On the other hand, random search provides a graph where there are little changes at certain years throughout the iterations. It make senses since the global particle only get updated when a new initialized particle has better fitness value. Thus, if there isn't any particle that is better then the global particle stay the same. Hence, the flat periods of the graph.

5 Conclusion

In this report, I implement the vanilla PSO algorithm and test different parameter compare to random search. For inertia value, negative or positive value does not affect the result, but lower value provides a rapid development while higher value gives a steady graph. Cognitive and social information provides the best result at the value of 1.496180 compared to 1.2 or 2.0. With little differences in terms of value, the cognitive/social can provide much drastic result. Additionally, the random search does not perform well as the particles are randomly initialized, but it does good enough when the parameters of the PSO are not correctly provided. Thus, to ensure a good result, PSO's parameters need to be accurately initialized since little differents can lead to significant differences in the final results.